The Impact of Climate Change on Electricity Demand in Thailand

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Abstract

Climate change is expected to lead to changes in ambient temperature, wind speed, humidity, precipitation and cloud cover. As electricity demand is closely influenced by these climatic variables, there is likely to be an impact on demand patterns. The potential impact of future changes in climate on electricity demand can be seen on an hourly, daily and seasonal basis through the fluctuation of weather patterns. However, the magnitude of such changes will depend on prevailing electricity use patterns as well as long-term socio-economic trends.

This thesis investigates how changing climate will affect Thailand's short-term and long-term electricity demand. Its review of available literature across the climate change and power systems fields highlights that analysis of such impacts for developing nations is almost entirely lacking. It then presents a modelling approach to capture the influence of temperature on daily and seasonal demand. The models are initially used to examine the sensitivity of demand to uniform rises in temperature. More sophisticated modelling, based on temperature projections from the UK Hadley Centre climate model combined with socio-economic projections from the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios, is used to project absolute changes in Thailand's electricity demand across three future time periods. The specific climate and socio-economic scenarios considered here indicate that mean annual temperatures in Thailand will rise by 1.74 to 3.43°C by 2080, implying additional increases in Thai peak electricity demand of 1.5–3.1% in the 2020s, 3.7–8.3% in the 2050s and 6.6–15.3% in the 2080s.. The implications of the changes are discussed in terms of Thailand's approach to meeting future electrical demand.

Declaration of Originality

I declare that this thesis has been completed by myself and that, except where indicated otherwise, the research documented is entirely my own.

Suchao Jake Parkpoom

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Korb khun kub

Contents Summary

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Glossary of Terms

AIM	Asian Pacific Integrated Model
AGCMs	Atmosphere General Circulation Models
AI	Artificial Intelligence
AMIP	Atmospheric Model Intercomparison Project
ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
CAIT	Climate Analysis Indicators Tool
CCGT	Combined Cycle Gas Turbine
CDD	Cooling Degree Day
CDH	Cooling Degree Hour
CFCs	Chlorofluorocarbons
CH_4	Methane
CO_2	Carbon Dioxide
DDC	Data Distribution Centre
DTR	Diurnal Temperature Range
EEE	Economy Energy Environment Model
EGAT	Electricity Generating Authority of Thailand
EGCO	Electricity Generating Company
EPPO	Energy Policy and Planning Office
ESI	Electricity Supply Industry
EU	European Union
GCC	Global Carbon Cycle
GCMs	General Circulation Models
GDP	Gross Domestic Product
GHGs	Greenhouse Gases
GNP	Gross National Product
GWP	Global Warming Potentials
GtC	Gigatons of Carbon

HadGCM	UKMet Office Hadley Centre
HCFCs	Hydro-Chlorofluorocarbons
HDD	Heating Degree Day
IIASA	International Institute of Applied Systems Analysis
IEEE	Institute of Electrical and Electronics Engineers
IIP	Index of Industrial Production
IPCC	Intergovernmental Panel on Climate Change
IPPs	Independent Power Producers
LA	Lignite Authority
LEG	Low Economic Growth
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MESSAGE	Model Energy Supply Strategy Alternatives General Environmental
MEA	Metropolitan Electricity Authority
MEG	Moderate Economic Growth
MiniCAM	Mini Climate Assessment Model
MLR	Multiple Linear Regression
MV	Moving Average
MOU	Memorandum of Understanding
NEA	Northeast Electricity Authority
N_2O	Nitrous Oxide
NWP	Numerical Weather Prediction
NWSNOAA	National Weather Station at the National Oceanic and Atmospheric Administration
NY	New York
OECD	Organisation of Economic Cooperation and Development
OGCMs	Ocean General Circulation Models
PEA	Provincial Electricity Authority
PE	Processing Elements
PFC	Perfluorocarbon

PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
SAR	Second Assessment Report
SE	Southeast
SF_2	Sulphur Hexafluride
SGCMs	Simple General Circulation Models
SPPs	Small Power Producers
SRES	Special Report on Emission Scenarios
TEG	Target Economic Growth
TF	Transfer Function
TVA	Tennessee Valley Authority
UNEP	United Nations Environment Programme
UNFAO	United Nations Food and Agriculture Organisation
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
UKCIP	UK Climate Impacts Programme
WMO	World Meteorological Organisation
YEA	Yanhee Electricity Authority

List of Symbols

θ_1, θ_2, θ_n	Moving average coefficients model parameters
ϕ_1, ϕ_2, ϕ_n	Autoregressive model parameters
ε_t	Random error term with zero mean and constant variance
α	Diurnal temperature range
ρ	Air density (kg/m^3)
$\beta(X)$	Constant Term
$\beta_1 \ldots\ldots \beta_n$	Intercept term regression coefficients
β_{CDH}	Gradient indicating
Day, Hour	Dummy variables
D_t	Electricity demand
Ele_0	Present demand (EJ/year)
Ele_{10}	Present demand final (EJ/year)
G	Growth rate of electricity demand (rate/year)
L_{actual}	Actual demand
$L_{forecast}$	Modelling demand
N	Number of hours
P	Power (W/m^2)
Pop	Population
Q_r	Input to the neuron
S	Time Period
t_{max}	Historic average monthly maximum temperature (°C)
t_{mean}	Historic mean monthly temperature each (°C)
t_{min}	Historic average monthly minimum temperature (°C)
T	Temperature (°C)
T_{act}	Historic temperature base year (°C)
T_{CC}	Temperature with climate change (°C)
T_b	Threshold temperature (°C)
$\Delta TMAX$	Change in monthly maximum temperature (°C)
$\Delta TMEAN$	Change in monthly mean temperature (°C)
$\Delta TMIN$	Change in monthly minimum temperature (°C)

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Chapter 2

Climate Change

Climate change or global warming is the greatest scientific and political challenge of the 21st century. The UK Government's Chief Scientist regards it as a "greater threat than terrorism"(BBC News, 2004). Despite the recent political activity, concern over climate change is not new. The Intergovernmental Panel on Climate Change (IPCC) was established in 1988, by the United Nations, the World Meteorological Organisation (WMO) and United Nations Environment Programme (UNEP) (Albritton and Filho, 2001). Its task was to:

1. assess scientific information relating to climate change,
2. assess its environmental and socio-economic consequences, and
3. to formulate strategies to respond to it.

Separate Working Groups were created for each of these tasks with many of the world's most eminent scientists directly involved in researching, writing or reviewing a series of four authoritative reports. The First Assessment Report was published in 1990, the Second Assessment Report in 1995 and the Third Assessment Report in 2001. The Fourth Assessment Report is currently being published although the summaries from each of the Working Groups have been released (IPCC, 2007a, IPCC, 2007b, IPCC, 2007c). The scientific evidence has grown more credible over time allowing the IPCC to issue increasingly firm statements regarding the role of human beings. The 1995 report stated significantly that "the balance of evidence suggests a discernable human influence on the climate system" (IPCC, 1995 WG1). By 2007 the IPCC views it as "very likely" (i.e., greater than a 90% chance) that "the global average net effect of human activities since 1750 has been one of warming".

This chapter aims to provide a background to the issue of climate change. It examines the basis of the greenhouse effect and the changes in concentrations of greenhouse gases that have led to recent changes in climate. It also looks at the potential evolution of the climate over the 21st century and the environmental, social and economic challenges that may bring.

2.1 Climate Change Science

2.1.1 Climate and the Greenhouse Effect

The climate is a description of average weather over a period of time together with its statistical variations (Houghton, 1997). The Earth's climate is driven ultimately by the Sun from which large amounts of solar energy come. Some of it is reflected back into space by the atmosphere but around 69% of the incident radiation is absorbed by the atmosphere and surface. The surface and atmosphere are warmed as a result and will themselves radiate energy back into space. The incoming and outgoing energy are in nature approximately in balance.

The "greenhouse effect" was recognised by Fourier in 1827 (Cowie, 2007), as the effect that was responsible for the Earth being warmer than it would be without an atmosphere. The effect is named as, rather like a greenhouse, it allows light energy in but traps heat to help plants grow. Although not known to Fourier it is now known that the presence of an atmosphere does not guarantee the trapping of heat rather it is the constituent parts within it. Earth's atmosphere is almost completely nitrogen and oxygen but it is the tiny quantities of specific "greenhouse gases" that create the effect. The process is natural and has been occurring on Earth for over two billion years with small amounts of water vapour and carbon dioxide (CO_2) trapping sufficient heat to allow water to exist as a liquid and create conditions suitable for life (Houghton, 1997; Hardy, 2004).

Although the greenhouse effect is a natural phenomenon, scientists and now politicians have concerns regarding the 'enhanced' greenhouse effect where increasing concentrations of CO_2 and other greenhouse gases trap greater amounts of heat, raising global temperatures. Following direct measurements at Mauna Loa in Hawaii it was noticed that atmospheric concentrations of CO_2 were rising. Further measurements from air trapped in Antarctic ice showed that concentrations have risen significantly since pre-industrial times when concentrations were approximately 280 parts per million by volume (ppmv). By 1998 concentrations were up by 27% to 366 ppmv and by 2007 were as high as 383 ppmv. The accelerating trend in concentration is shown very clearly in Figure 2.1.

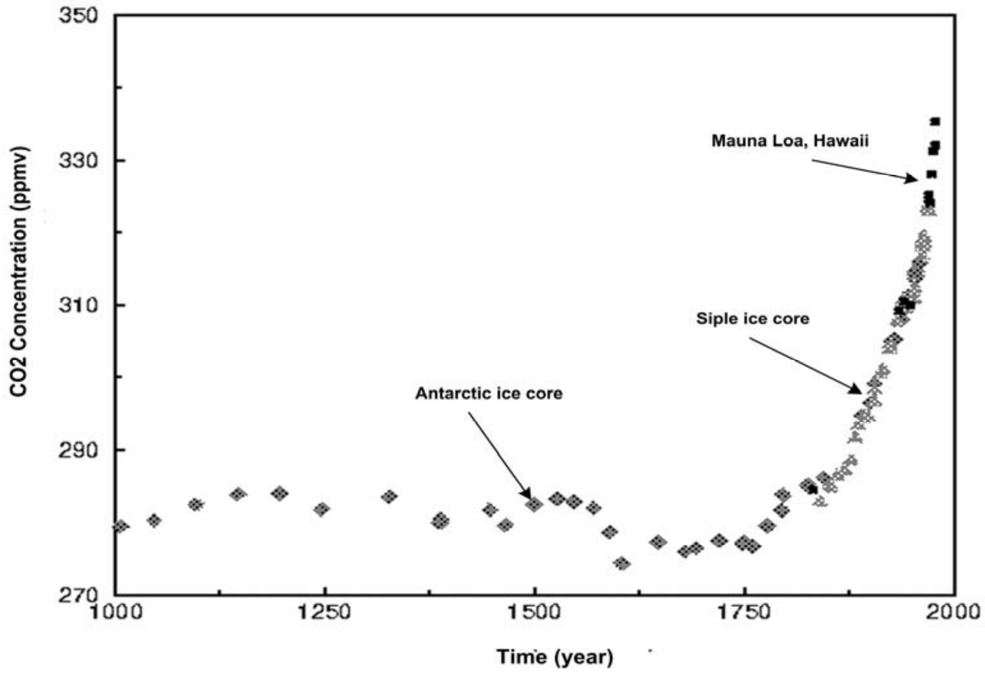

Figure 2.1: Atmospheric CO_2 since 1000 AD as indicated by Antarctic ice samples and direct measurements at Mauna Loa, Hawaii (Keeling et al.,1976).

2.1.2 The Global Carbon Cycle

The carbon cycle is the process of exchange of CO_2 between a range of naturally-occurring carbon reservoirs. As illustrated in Figure 2.2 these reservoirs include the atmosphere, oceans, living organisms and, over long time-scales, sediments and rocks. The amount of carbon stored in these is immense: the atmosphere holds around 750 gigatons of carbon (GtC), terrestrial vegetation and soils 2,190 GtC, surface ocean a further 1,020 GtC. The largest store is the deep ocean which contains an order of magnitude more carbon at around 38,100 GtC. (Houghton, 1997).

There are many processes that transfer CO_2 between the reservoirs including the exchange of gases between atmosphere and ocean, respiration, photosynthesis, and microbial breakdown of dead organic matter and soil carbon. The largest flows are between the atmosphere and deep water of the ocean and the atmosphere and land vegetation. Carbon is taken from the atmosphere through photosynthesis where plants take in CO_2, convert it into carbohydrates and release oxygen. A similar photosynthesis process occurs with marine phytoplankton which is both responsible for the lives of organisms in the ocean and much of the oxygen present in the Earth's atmosphere. Carbon is released back into the atmosphere through the respiration of animals or through the release of the dissolved carbon dioxide from the oceans as the water becomes warmer.

It can be seen from Figure 2.2 that the mass flow of carbon between the reservoirs is much smaller than those in storage. As such, small changes in the land or ocean reservoirs could have a greater effect on the cycle. It is for this reason that there is concern regarding the carbon released into the atmosphere from long term storage in fossil fuel deposits through fossil fuel burning and from the soil through changing land use.

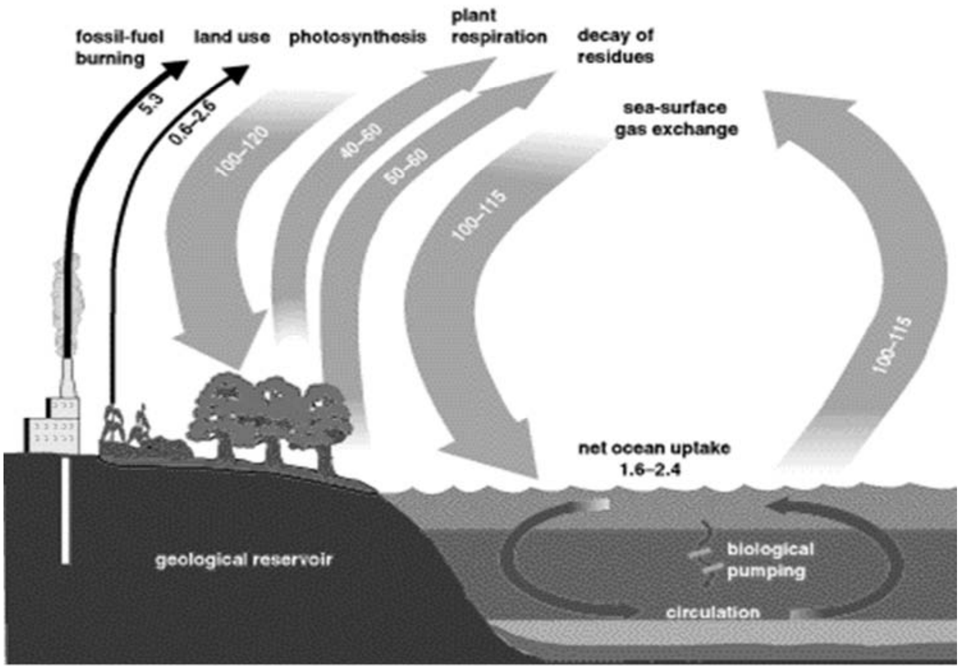

Figure 2.2: Global carbon cycle and annual flows. GtC/yr over 1980-1989 (Post et al., 1990).

Fossil Fuel Emissions

Fossil fuels are burned to produce energy and provide most of our current energy needs. Created from decayed organic matter, they are non-renewable and have a remaining lifetime of 40 to 200 years, although there is a great deal of uncertainty over these lifetimes. The three main types of fossil fuels are oil, coal and gas. Among the fossil fuels, coal produces the most CO_2 per unit of energy while natural gas produces the least (Houghton, 1997). Emissions of greenhouse gases from fossil fuels occur globally with more than 80% coming from transportation and industrial sources, primarily electricity generation, and another 20% from deforestation and biomass burning.

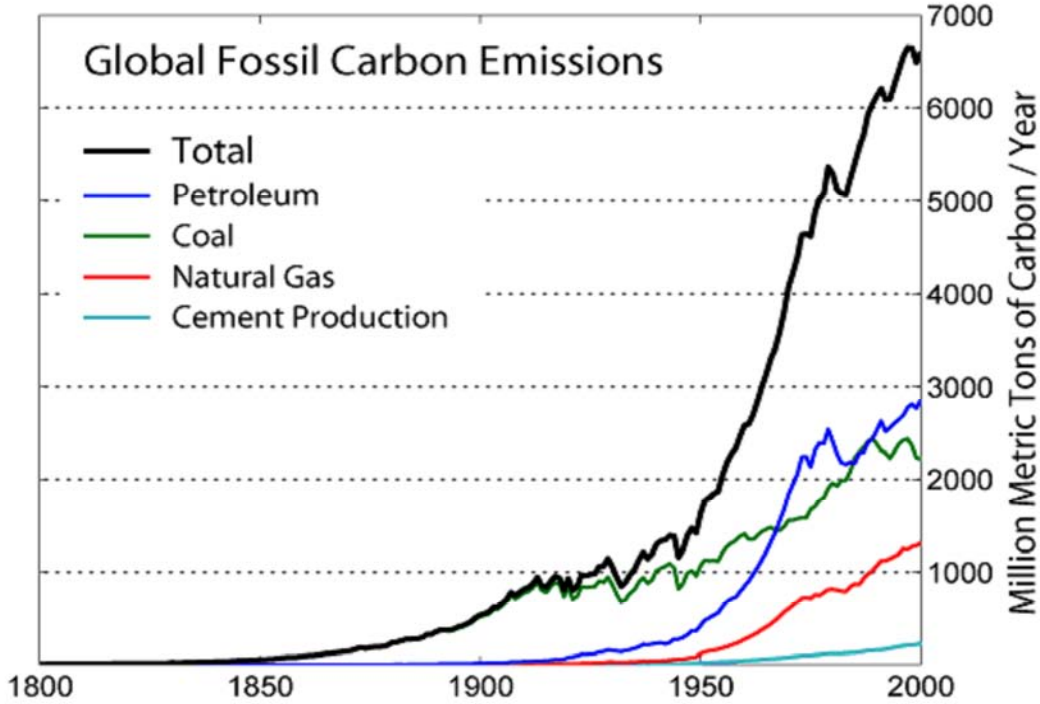

Figure 2.3: Global carbon emission from fossil fuel combustion and cement production (Marland et al., 1999).

Figure 2.3 illustrates the emissions of carbon since 1800, part-way through the Industrial Revolution. From around 1850 emissions can be seen to be growing rapidly other than during a flat period in the early 1900s around the time of the First and Second World Wars. The initial growth was in coal which was used in increasing volumes to raise steam to power factories, steel works and rail and water transport. From around 1900, petroleum use grew very rapidly for vehicle fuels and chemicals and overtook coal in the 1960s. Natural gas use has grown more steadily but has increasingly been used for heating and more recently for power generation.

The combination of the three fuels has resulted in global fossil carbon emissions reaching 6,700 million tonnes of carbon (MtC) in 2000 compared to 1,400 MtC in 1950. The world population is about 6 billion so the average fossil fuel emission is about one tonne of carbon per person per year or 3.67 tonnes of CO_2 per person per year (Houghton, 1997). There is major imbalance in use, however, as the top ten CO_2-emitting countries account for 66% of the total global emissions. The United States accounts for 23% alone with China and India rapidly gaining ground (Figure 2.4) (Hardy, 2004). The United Kingdom accounts for around 2% of global carbon emission. With energy use strongly linked to economic and population growth, the emissions can only grow.

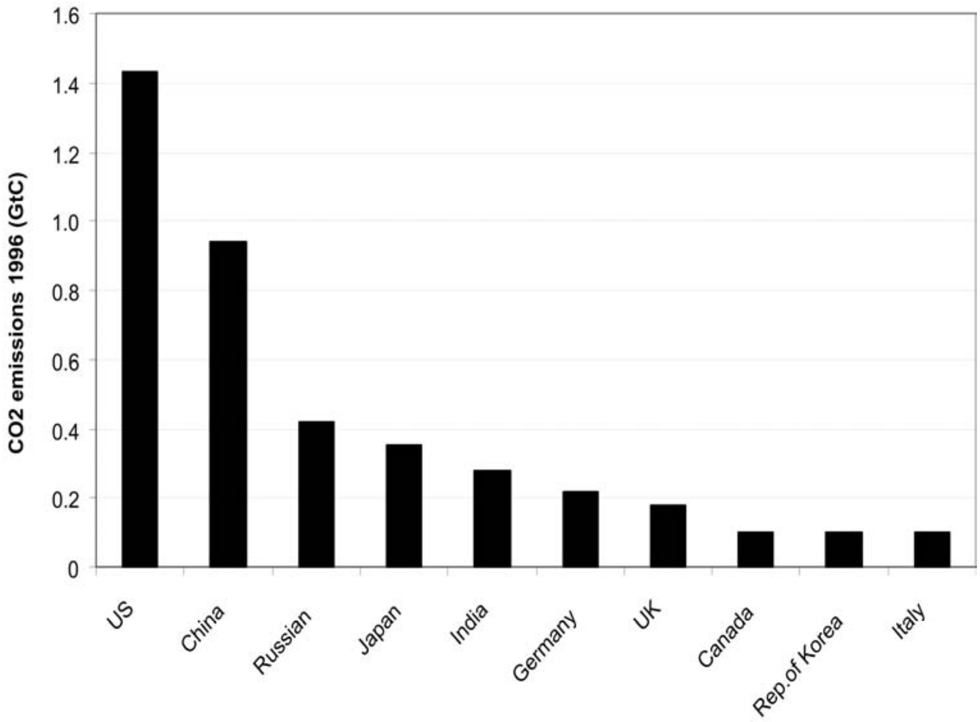

Figure 2.4: The top ten countries for CO_2 emissions (Hardy, 2004).

Land-use Change

Change of land use is considered one of the most important anthropogenic effects especially in tropical countries. It is estimated that the amount of carbon held per unit area by the soil and vegetation of natural forests is about 20 to 100 times more than agricultural land. Exploitation of minerals and timber lead to major clearance of large forest areas. In the past two decades, the need for agricultural land has increased as the population has grown especially in developing countries which rely on development of forested areas. The loss of forests is damaging not only because of the land degradation but also because of the contribution that loss makes to global warming (Houghton, 1997). The loss of forests also means the loss of over half of the world's species that live in tropical forests. Another potential form of damage is the reduction in rainfall. The measurements from satellites have provided estimates of the area of tropical forest lost. In the 1980s, the average loss was 1% per year as shown in Table 2.1 (Hardy, 2004).

Continent	Forest area 1980	Forest area 1990	Rate of change 1981-1990 (%)
Thousands of square kilometres			
Africa	6,500	6,000	-0.8
Latin America and Caribbean	9,230	8,400	-0.9
Asia	3,210	2,750	-1.2
Total	18,840	17,150	-0.9

Table 2.1: The estimates from the United Nations Food and Agriculture Organisation (UNFAO) of forest cover and deforestation for 87 countries in tropical regions (Quoted in *The World Environment 1972-1992* eds. Tolba and Kholy-El, 1992).

Greenhouse Gases and Climate Change

The key idea in the science underlying climate change is that greater concentrations of greenhouse gases will lead to increasing temperatures. Instrumental records over the past 150 years (since the start of large-scale industrialisation) indicate rising atmospheric greenhouse gas concentrations (carbon dioxide, methane, nitrous oxide and also man-made gases). These have been accompanied by a long term trend of rising temperatures although there has been some fluctuation. It is widely regarded that increasing greenhouse gas emissions are driving temperature rise but positive feedback within the climate system means that the opposite is also true: that rising temperatures can result in higher concentrations of greenhouse gases.

Deuterium (an isotope of hydrogen) concentrations from ice samples can be used to estimate historic temperatures. Figure 2.5 shows data from the last 420,000 years from ice cores from the Antarctic for both temperature and CO_2 concentrations. The diagrams show that the trends for temperature and CO_2 are very similar.

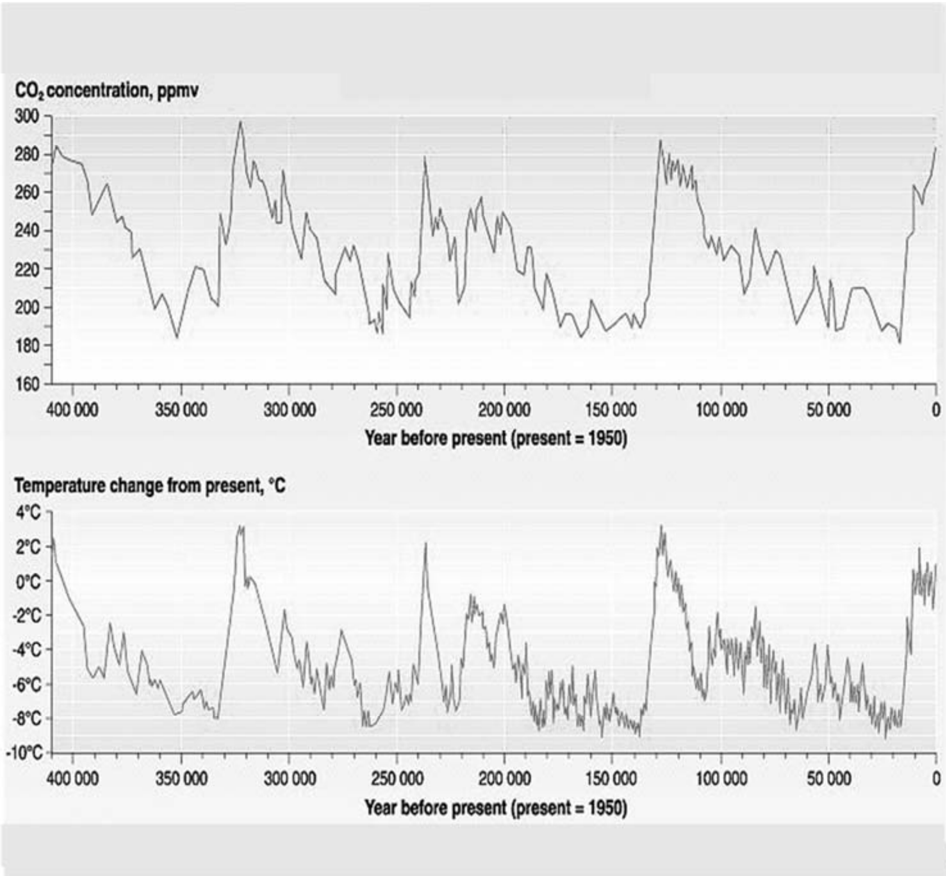

Figure 2.5: Temperature changes (bottom) and CO_2 concentration over last 420,000 years, indicated by ice cores from Vostok, Antarctica (Barnola et al., 1999; Petit et al., 2000).

2.1.3 Key Greenhouse Gases

Carbon dioxide, methane and nitrous oxide are continuously emitted into the atmosphere. Their significant growth is shown in Table 2.2 and explained in more detail below.

Carbon Dioxide

Carbon dioxide is the most important greenhouse gas and the greatest emitters of CO_2 in industrialized nations are power plants, jet aircraft, factories and motor vehicles. Other carbon dioxide emitters include forest clearing, biomass burning and some non-energy production processes such as the production of cement. Table 2.2 shows that concentrations of CO_2 increased by 31% to 365ppmv since pre-industrial times up to 1998. Further growth in emissions to 2007 (IPPC, 2007) has seen concentrations at 383 ppmv (37% above pre-industrial times). The warming effect of the CO_2 can be described as its radiative forcing quantified as a heating effect per unit area of incident sunlight (Table 2.2). Table 2.3 presents an assessment of global CO_2 flows for the 1980s and 1990s. It shows that not all of the emissions from fossil fuel burning have increased atmospheric concentrations and that the oceans have absorbed a significant amount as has uptake from the land.

Gas	Amount by volume	Increase over pre-industrial (1750)	Percentage increase	Radiative forcing (W/m^2)
CO_2	365ppm	87ppm	31%	1.46
Methane	1,745ppb	1,045ppb	150%	0.48
Nitrous Oxide	314ppb	44ppb	16%	0.15

Table 2.2: Greenhouse gas concentrations present in 1998 (IPCC, 2001).

	1980s	1990s
Atmospheric increase	3.3 ± 0.1	3.2 ± 0.1
Emissions (fossil fuel, cement)	5.4 ± 0.3	6.4 ± 0.4
Ocean-atmosphere flux	-1.9 ± 0.6	-1.7 ± 0.5
Land – atmosphere flux	-0.2 ± 0.7	-1.4 ± 0.7

Table 2.3: Estimates of global CO_2 balance for the 1980s and 1990s based on intra-decadal trends in atmospheric concentrations (Prentice et al., 2001).

Methane Emission (CH_4)

Methane (CH_4) is a colourless and odourless gas. It is another greenhouse gas with both natural and man-made sources. Natural sources include wetland soils and coastal sediments. Man-made sources include agriculture such as rice cultivation, natural gas activities, solid waste and landfills. The energy released by methane in the form of natural gas is used to heat buildings and to generate electrical power. Atmospheric methane concentrations have increased by about 150% since 1750 and are increasing rapidly by 1.1% per year (Hardy, 2004). Methane concentrations continue to increase, from 1,610 ppb in 1983 to 1,745ppb in 1998, but the observed annual increase has declined during this period. Methane is removed from the atmosphere by reacting with the hydroxyl radical (OH) and is ultimately converted to CO_2 (U.S. Greenhouse Gas Inventory Program 2002). The IPCC has estimated that most of the CH_4 released into the atmosphere results from human activities such as agriculture, fossil fuel use and waste disposal (IPCC, 2001) as Figure 2.6 shows (Houghton et al., 2001).

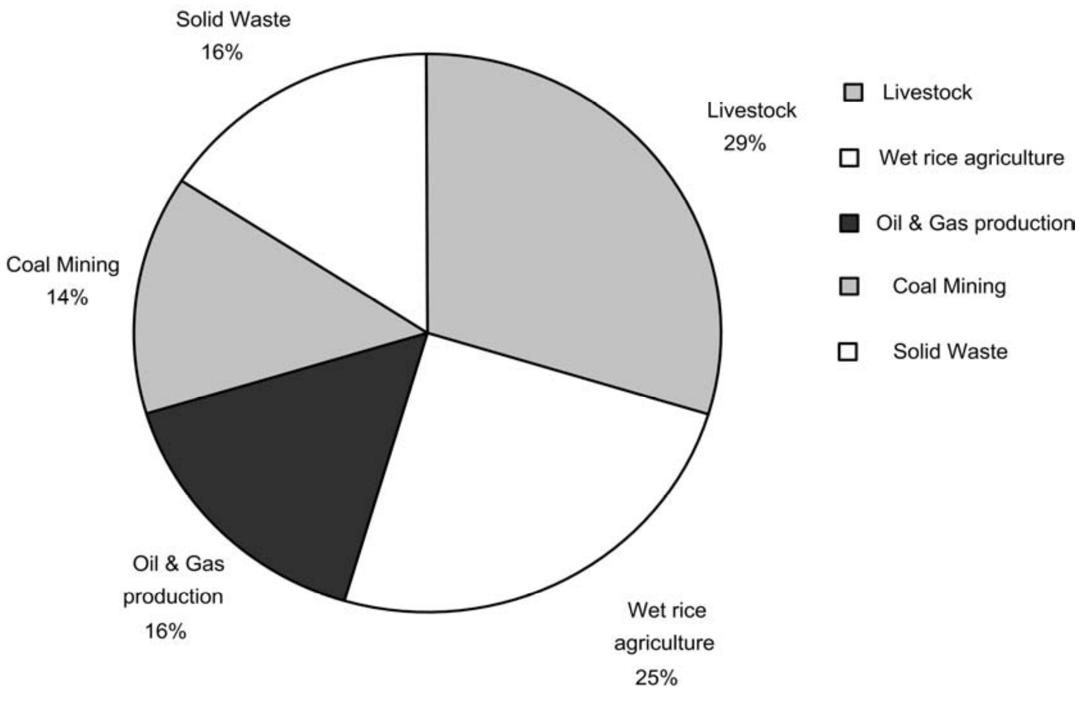

Figure 2.6: Anthropogenic sources of methane (WRI, 2002).

Nitrous Oxide (N_2O)

Nitrous Oxide (N_2O) is best known as 'laughing gas' and its atmospheric concentration has steadily increased during the Industrial Era. It is now 19% larger than in 1750, from a pre-industrial value of about 270 ppb to 314 ppb in 1998 (Prentic et al., 2001). Atmospheric measurements and evidence from the pre-industrial era suggest that increases in N_2O are due mostly to human activity: chemical production, agricultural soils, deforestation, biomass burning, fossil fuel combustion particularly in vehicles and power stations, wastewater treatment and waste combustion. Although N_2O is broken down by light in the stratosphere its lifetime can reach up to 150 years in the atmosphere (U.S. Greenhouse Gas Inventory Program, 2002).

Halocarbons

Chlorofluorocarbons (CFCs) and Hydro-Chlorofluorocarbons (HCFCs) are also greenhouse gases. CFCs are man-made chemicals, the main cause of stratospheric ozone depletion and have a lifetime of 60 to 100 years (Hardy, 2004). CFCs are non-toxic and non-flammable and have been used widely as coolants in air conditioners and refrigeration, aerosols, foam in fire extinguishers, and as liquid in cleaning products. As the concentration of CFCs in the atmosphere built up in to 1ppbv (parts per billion) it was noticed that the ozone layer was becoming depleted. As the ozone layer plays a major role in shielding the lower atmosphere from cosmic radiation there was widespread concern which resulted in the Montreal Protocol which bans CFC use. HCFCs and other related chemicals such as Perfluorocarbon (PFC) which are considered as a substitute for CFCs are very strong greenhouse gases. Although they currently contribute little to warming, increasing use could eventually contribute several percent to the warming effect (IPCC, 2001.).

Global Warming Potential

Global warming potentials (GWP) measure the relative impact of greenhouse gases over different time periods (Shine et al., 1990). The intention of GWPs is to have an ability to trace gas emissions to see the effects of direct and indirect radiative forcing. For example, GWPs could be verified to estimate the effect of a given reduction in CO_2

emissions compared with a given reduction in CH_4 emissions, for a specified time horizon. Table 2.4 presents the GWPs presented in the IPCC Second Assessment Report (IPCC, 2001) for a 200 year time horizon. CO_2 is defined as having a GWP of 1. The GWP of other greenhouse gases is then measured relative to the GWP of carbon dioxide. Other greenhouse gases have much higher GWP than carbon dioxide, but because their concentration in the atmosphere is much lower, carbon dioxide is still the most important greenhouse gas, contributing about 60% to the enhancement of the greenhouse effect. Sulphur hexafluoride (SF_6), used in electrical circuit breakers, has a large GWP of 23,900 and an atmospheric lifetime of 3,200 years (Scimel et al., 1996).

Greenhouse gas	Concentration 1800s-2000	Anthropogenic Sources	GWP	Percentage Effect
Carbon Dioxide	280-370ppm	Fossil fuel burning, Deforestation	1	60%
Methane	0.75-1.75ppm	Agriculture, Fuel leakage	21	20%
Halocarbons	0-0.7ppb	Refrigerants	3400+	14%
Nitrous Oxide	275-310ppb	Agriculture, Combustion	310	6%
Ozone	20-30ppb	Urban Pollution	-	-

Table 2.4: Summary of key greenhouse Global warming Potentials (Shine et al., 1990).

2.1.4 Climate Processes and Feedback

Analysis of climate change would be far simpler were it not for the complexity of the climate system and specifically the existence of climate feedback mechanisms associated with temperature increases. Feedbacks can be positive or negative according to the global energy balance between the incoming heat from the sun and outgoing heat from the earth. The most important feedbacks result from water vapour, clouds, stratosphere, ocean, and land surface.

Water Vapour

Water vapour is the most important factor in climate change feedback as a warmer atmosphere will encourage water evaporation from the ocean and water surfaces and water vapour and rainfall will increase. This appears to be already happening as global land precipitation has increased by 2% since 1900 (Hardy, 2004). Water vapour is a powerful greenhouse gas and creates a positive feedback, which on its own would increase the global average temperature rise by about 60 percent when compared to CO_2 alone (Houghton, 1997).

Clouds

A change in surface air temperature and ocean evaporation is likely to increase or decrease the clouds. For instance, increased cloud cover (the blanketing effect) will result in warmer winters (when cloud traps heat) and cooler summers (when clouds tend to reflect the solar energy) (Nicholls et al., 1996). The opposite occurs when the cloud cover decreases. The clouds absorb infrared radiation emitted from the surface and re-emit their own radiation, but the amount re-emitted is smaller than the amount absorbed because the tops of clouds are colder than the underlying surface (Harvey, 2000). High clouds tend to have a net warming effect while low clouds have a net cooling effect. The overall effects of clouds can be both positive and negative depending on the changes of cloud cover, the height of the existing clouds and temperature.

Snow and Ice

On a warmer land and sea surface more snow and ice will melt. There is much evidence showing the decline of snow cover and sea-ice cover. In Africa, for example, the alpine glaciers of Mount Kenya lost 75% of their area between 1899 and 1987 with 40% of the loss occurring between 1963 and 1987 (Hastenrath and Krus, 1992). Changes in the rate of ice loss from Alaskan glaciers have doubled leading to sea-level rises (Arendt et al., 2002) and 10% decline in annual snow cover over the Northern Hemisphere during the past 20 years (Groisman et al., 1994). During the last 100 years in the Northern Hemisphere, the extent of summer sea ice has decreased 15%

(Gloersen and Campbell 1991). Summer 2007 shows a record low in Arctic ice coverage with the Northwest Passage now passable to non-icebreaking ships (NSDIC, 2007).

The loss of snow and ice creates a positive feedback increasing the global average temperature rise relative to CO_2 alone by about 20 percent (Houghton, 1997). This is because snow and ice tends to have a higher albedo (reflectivity) than snow-free surfaces, so a reduction in snow and ice-cover leads to an increase in the amount of solar radiation that is absorbed at the surface. Research suggests that changes in snow cover will depend on changes in precipitation, cloud cover and location. Changes in the nature of sea ice will also depend on changes of heat flow between the ocean and the atmosphere.

Ocean

Change in global precipitation and temperature rises could affect large-scale oceanic circulation patterns (Weaver, 1993). The ocean is the main source of water vapour and the main heat source for the Earth's climate. In comparison, the entire heat capacity of the atmosphere is equivalent to less than 3 metres depth of water (Houghton, 1997). When the air surface is warm, the ocean tends to warm much more slowly resulting in less evaporation and a decrease in rainfall. The heat absorbed by the oceans will have significant impact on the climate system.

As Table 2.3 indicated, the oceans have absorbed a significant amount of the CO_2 emitted into the atmosphere. However, as the concentration of CO_2 in the ocean increases, there is a risk that its ability to absorb CO_2 will reduce, potentially making global warming worse (Harrabin, 2007). This appears to be happening as researchers from the University of East Anglia have reported that the amount of CO_2 absorption has reduced. The results from a 10 year study in the North Atlantic show CO_2 uptake halved between the mid-90s and 2000 to 2005 (Harrabin, 2007).

The Gulf Stream system is one of the world's most important climate features. It is a warm surface ocean current that travels in a north-easterly direction across the Atlantic

Ocean. The Gulf Stream helps to decide the direction and magnitude of global ocean currents. For example, for the UK and northwest Europe, it influences the climate by delivering relatively humid and mild air. The surface wind is driven by changes in water density on the ocean surface in the north Atlantic, cooled by winds from the Arctic.

Land Surface

When the temperature rises, it is likely to affect the state of the atmosphere and land surface such as soil moisture, roughness and vegetation. Change in land-surface cover affects land-atmosphere exchanges of radiation, momentum, heat, water vapour, precipitation and cloud properties. Other changes in land surface, e.g., large-scale deforestation in tropical regions (South Asia and Africa) could affect the global climate as it increases the temperature of the Earth's surface and decreases evaporation (Harvey, 2000).

2.2 Recent Climate Change

2.2.1 Atmospheric Temperature Rise

The global averaged surface air and sea temperature has risen by between 0.3 and 0.6°C since 1850 (Houghton et al., 1990; Houghton et al., 1992). The twentieth century was the warmest, and the years 1990 to 2000 had most of the hottest years on record. The IPCC's first report in 1990 suggested the global averaged temperature increases between 0.15 to 0.3°C per decade for 1990 to 2005 (IPCC, 2007).

Figure 2.7 shows the measured global surface temperatures from 1856 to 2005. Year 1998 was the warmest in the series at over 0.6°C above the 1961-1990 mean. The 5 yearly moving average temperatures has been increasing in almost all periods apart from a few years in the 1940s. The decreases in the 1940s appear to have been caused by a rise in concentration of sulphate aerosols in the atmosphere from volcanic eruptions. The sulphate aerosols have a cooling effect on the climate because they scatter light from the Sun, reflecting its energy back out into space (Brahic, 2007). In the

United States (Bellingham and Washington), the average global land and marine surface temperature increased by 2.2°C between 1920 and 1997 (Hardy, 2004). The existing concentrations of greenhouse gases mean that further warming is guaranteed. Warming of around 0.2°C per decade is projected even if the concentrations of all greenhouse gases and aerosols are kept constant at year 2000 levels (IPCC, 2007).

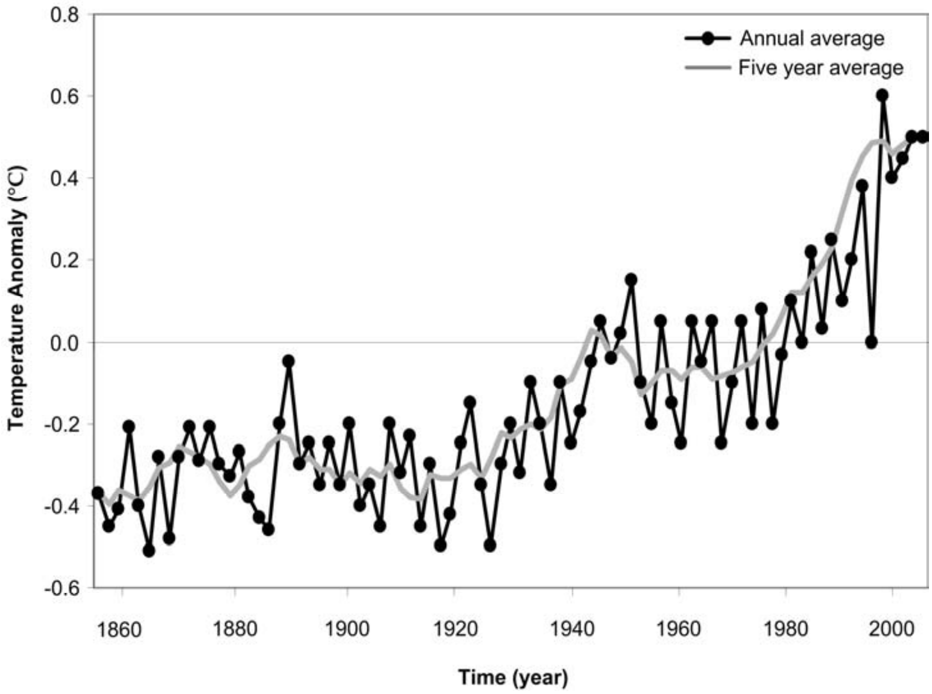

Figure 2.7: Measured global surface temperatures from 1856 to 2005. Solid line represents five year moving average (Jones and Moberg, 2002).

2.2.2 Precipitation Changes

Precipitation on the land surface has increased by about 0.5 to 1% per decade in much of the Northern Hemisphere. Other precipitation indicators suggest that large parts of the tropical oceans have had more precipitation in recent decades, and that precipitation has significantly increased over tropical land areas during the 20th century at about 2.4 percent per century (Nicholls et al., 1996). The changes in precipitation are more complex than temperature changes. Highly variable rates of precipitation and enormous spatial variability makes determination of mean precipitation difficult (Nicholls et al., 1996).

2.2.3 Extreme Weather Change

Extreme climate events observed include: droughts, floods, storms, as well as very hot and very cold periods. The changes which are likely to have the most impact are those connected with the hydrological cycle (Houghton, 1994). Drought is caused by reduced rainfall and could be made much worse by rising temperatures which will lead to increased evaporation and lower surface moisture. On the other hand, heavy rainfall and thunderstorms will lead to floods. Frequent and intense storms are also caused by warmer sea temperatures.

2.3 Predicting Climate Change

The calculation of the effects in the climate system is the key to projecting the impact of climate change on humans. The climate system itself is complex and some driving factors still remain uncertain such as the future rates of economic growth and fossil fuel combustion. Feedbacks will also affect climate change. Several methods have been used to predict the future climate.

- Palaeo-analogue methods which use proxy data to estimate future climate change from past climates
- Simple global-average models
- Simulations with Global Circulation Models (GCMs)

The first method, palaeo-analogue, determines the sensitivity of climate to CO_2 concentrations from estimates of CO_2 concentrations and global average temperatures during periods in the past. Due to altered land-ocean proportions, adjustments in the prevailing temperature will have to be made to account for differences in the radiance of the sun and in the albedo of the earth. Simple global-average models of the carbon cycle were the standard method used to determine the future concentrations of CO_2 in the first and second IPCC assessments. Since then Global Circulation Models (GCMs) have been the main way of projecting climate (Cubasch and Cass, 1990).

2.3.1 Global Circulation Models

Computer models are widely used in predicting climate change due to their potential accuracy and precision. General Circulation Models (GCMs) use the same principles as numerical weather prediction (NWP) models where Newton's laws of conservation of momentum, conservation of heat and mass, and the gas law, are used to analyse the behaviour of the atmosphere and ocean. General Circulation Models are numerical computer models of the atmosphere and ocean used to predict the future climate patterns. The horizontal variation of the variables in each layer is determined either at particular grid points defined by latitude and longitude or by a number of mathematical functions.

The most complex models are known as the three-dimensional atmospheric general circulation models. Simple general circulation models (SGCMs) are used to study atmospheric processes within a simplified framework but are not suitable for future climate projections. Atmospheric general circulation models (AGCMs) and ocean general circulation models (OGCMs) divide the atmosphere or ocean into a horizontal grid with a typical resolution of 2-4^o latitude by 2-4^o longitude and typically 10-20 vertical layers (Hardy, 2004). Table 2.5 shows the resolution of the generation of ocean and atmosphere GCMs. Coupled atmospheric ocean general circulation models (AOGCMs) automatically compute the fast feedback processes (water vapour, clouds, seasonal snow and ice) as well as the uptake of heat by the oceans, which delays and distorts the surface temperature response but contributes to sea level rise through expansion of ocean water as it warms (McAvaney, 2001).

Centre	Country	Resolution and vertical levels	
		Atmospheric GCM	Ocean GCM
CCC	Canada	3.8° × 3.8°, 10 levels	1.8° ×1.8°, 29 levels
CSIRO	Australia	3.2° × 5.6°, 9 levels	3.2° × 5.6°, 21 levels
GFDL	USA	2.25° × 3.75°, 14 levels	1.875° × 2.25°, 18 levels
GISS	USA	4.0° × 5.0°, 9 levels	4.0° × 5.0°, 13 levels
MRI	Germany	2.8° × 2.8°, 30 levels	2.0° × 2.5°, 23 levels
Hadley Centre	UK	2.5° × 3.75°, 19 levels	1.25° × 1.25°, 20 levels

Table 2.5: Example GCMs, their spatial resolution (latitude × longitude) and number of vertical levels (McAvaney, 2001).

2.3.2 Model Evaluation

The different parameterisations of the strength of feedback mechanisms cause the differences in simulations. The ability of climate models, particularly AGCMs, to simulate mean distributions of climate variables has been improving. The IPCC Second Assessment Report (SAR) described comparisons between different coupled and component atmosphere GCMs in simulating current climate. The large scale seasonal distribution of surface air temperature is simulated on average by coupled models.

Table 2.6 below shows the spread of global model means. It also shows that higher mean temperatures tend to be accompanied by higher precipitation rates. Coupled models simulate mean sea level pressure well, but appear to have difficulty reproducing seasonal snow and ice cover, which has implications for the snow-ice feedback mechanism (Nicholls et al., 1996).

Group	Surface air temperature (°C)		Precipitation (mm/day)	
	Dec. Jan. Feb.	Jun. Jul. Aug.	Dec. Jan. Feb.	Jun. Jul. Aug.
CSIRO	12.1	15.3	2.73	2.82
GFDL	9.6	14.0	2.39	2.50
GISS	13.0	15.6	3.14	3.13
NCAR	15.5	19.6	3.78	3.74
Hadley Centre	12.0	15.0	3.02	3.09
Observed	12.4	15.9	2.74	2.90

Table 2.6: Coupled model simulated global average temperature and precipitation (Gates et al., 1996).

The IPCC Second Assessment presents the results of a comparative study of atmospheric models carried out for the Atmospheric Model Intercomparison Project (AMIP) (Gates, 1992). All models used standard condition of CO_2 and other factors. Table 2.7 is a summary of several key climatic variables. It can be seen that the models do not give identical pressure, temperature and precipitation. (Q 13)

Some indication of uncertainty in the projections can be obtained by comparing the responses among models (Cubasch and Meehl, 2001). The main uncertainties in model simulations arise from the difficulties in adequately representing clouds and their radiative properties, the coupling between the atmosphere and the ocean, and detailed processes at the land surface (Gates et al., 1996)

Model	Dec. Jan. Feb.		Jun. Jul. Aug.	
	North	South	North	South
Mean sea level pressure (mb)	1.4	1.4	1.3	2.4
Surface air temperature (°C)	2.4	1.6	1.3	2.0
Precipitation (mm/day)	0.80	0.71	0.62	0.77
Cloudiness (%)	10	21	14	16

Table 2.7: Root mean square error between observed variable and mean AGCM simulation (Gates et al., 1996).

2.3.3 Special Report on Emission Scenarios

Given the variation in the output from GCMs, the third IPCC assessments were based on a more structured approach to projecting climate. This aimed to introduce methods of handling uncertainties not only in GCM models but also in future CO_2 emissions driven by socio-economic and technical trends. The structured approach resulted in the publication of the IPCC Special Report on Emission Scenarios (SRES) (Nakicenovic and Swart, 2000; IPCC, 2001).

The report details a series of socio-economic and technical possibilities for the 21st century and the associated climate change they imply. As Figure 2.8 shows, a series of 'driving forces' influence climate outcomes; these are: population, economy, technology, energy and agriculture. Different possibilities are grouped together based on assumptions regarding the driving forces: these are known as the four SRES 'storylines' A1, A2, B1 and B2. The storylines are described by two trends: the first trend is whether the future is based on strong economic or strong environmental values; the second trend is whether the future is described in terms of increasing globalisation and increasing regionalisation. These storylines are summarised as follows (Nakicenovic and Swart, 2000; IPCC, 2001):

- A1 is a future of strong economic growth with the introduction of efficient technologies, and a global population that peaks in the middle of the century.
- A2 is a regionally diverse world with continuously increasing global population and regional economic growth.
- B1 is a convergent world with the same global population as in the A1 storyline but with rapid changes in economic structures and information, and increasing resource efficiency.
- B2 is a world in which the emphasis is on local solutions to sustainability, with continuously increasing population but at a lower rate than A2.

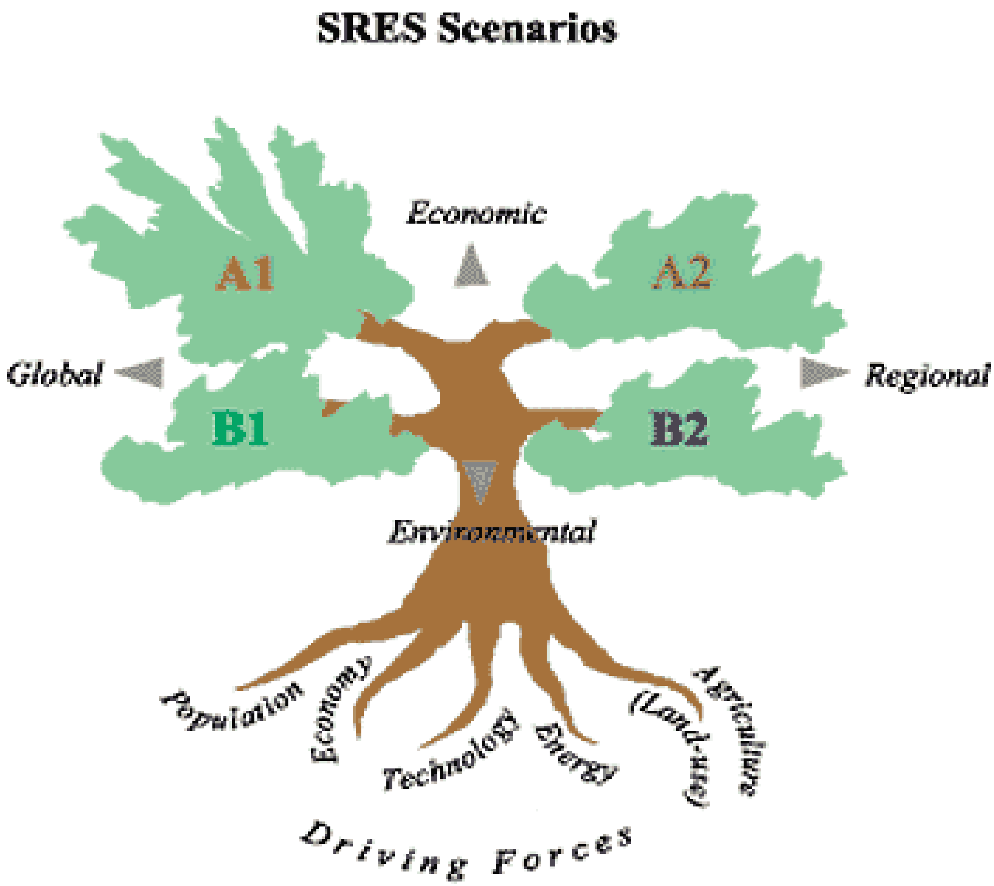

Figure 2.8: Schematic illustration of the four SRES storylines (Nakicenovic, 2000).

For each storyline, different scenarios were developed using six representative Economy-Energy-Environment (EEE) models to capture the current range of uncertainties of future GHG emissions, arising from different modelling approaches as well as uncertainties about driving forces. A total of forty SRES scenarios were developed and each is regarded as equally valid. In addition, a range of GCM models were used to translate the influence of the differing scenarios into projections of future climate. In this way the SRES approach aimed to incorporate uncertainty in modelling approaches as well as the very large uncertainty in future global development paths.

Together the SRES scenarios cover a very wide range of socio-economic paths and climate outcomes. Table 2.8 summarises the range of population and economic growth possibilities and the CO_2 concentrations, temperature changes and sea level rise projections that are consistent with them it can be seen that the range in possibilities becomes larger further into the future which reflects the very different paths taken by the storylines. By 2100 population is projected to be somewhere between 7 and 15 billion and GDP between 10 and 26 times larger than that in 1990. The climate impacts tend to follow this with larger populations and economic growth implying more significant changes: CO_2 levels may be between 478 and 1099 ppm with average global temperatures rising by 1.4 to 5.8°C and mean sea levels rising by up to 88 cm.

Year	Global Population (billions)	Global GDP (10^{12} US$/yr)	Per capita income ratio	CO_2 concentration (ppm)	Global temperature change (°C)	Global sea-level rise (cm)
1990	5.3	21	16.1	354	0	0
2000	6.1-6.2	25-28	12.3-14.2	367	0.2	2
2050	8.4-11.3	59-187	2.4-8.2	463-623	0.8-2.6	5-32
2100	7.0-15.1	197-550	1.4-6.3	478-1099	1.4-5.8	9-88

Table 2.8: The SRES scenarios and the implications for CO_2 level, climate and sea level (McCarthy, 2001).

The results from the model runs are made available on the IPCC Data Distribution Centre (DDC) (IPCC, 2007), website along with the climate projections. This is to allow their use in climate impacts assessment such that the impacts projected reflect the socio-economic and technical drivers.

2.4 Projections of Future Climate Change

2.4.1 Global Average Temperature Change

The IPCC SRES emission scenarios were applied to a range of GCMs which produced estimates of temperatures to 2100 and beyond. The range of global average temperature changes projected by the SRES scenarios and GCMs is between 1.4 and 5.8°C by 2100 depending on the climate sensitivity (Cubasch and Meehl, 2001). The expected range of temperatures falls towards the middle of this band - between 2.0 and

4.5°C by 2100. Figure 2.9 shows the range of potential rises for global average surface air temperature up to 2100. The temperature change for the highest latitudes may be double the global average. Climate change is unlikely to halt then. In fact most of the curves in Figure 2.9 indicate rapid temperature rises in 2100, and it is likely that the temperature will rise for the next century, again linked to greenhouse gas concentrations (Hardy, 2004).

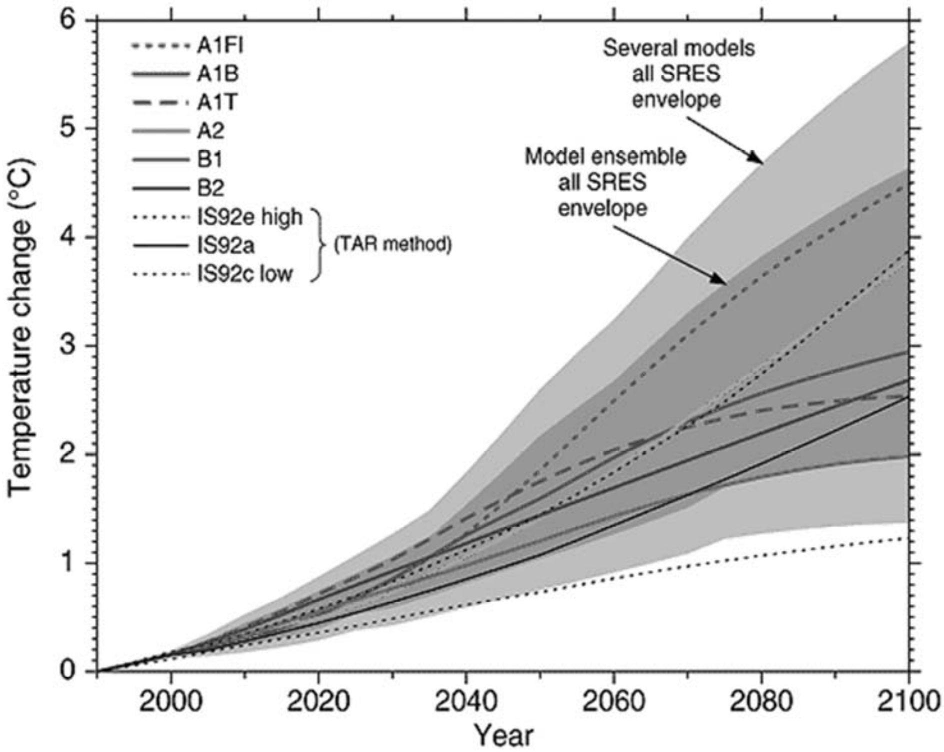

Figure 2.9: Projected global average surface air temperature increase from 1990 to 2100 (Cubasch and Meehl, 2001).

2.4.2 Sea Level Rise

At the end of the ice age 18,000 years ago, the sea level was 100m lower than the present time, as the water was contained within the polar ice-sheets. It is predicted that if all glaciers outside Antarctica and Greenland were to melt, the sea level rise between 1990 and 2100 would be 0.8 to 30cm with a central value of 20cm (Houghton, 2005). In addition to non-polar glacier melting, sea level rise will occur mainly because of thermal expansion of sea water, ice cap and glacier melting, and changes in the ice cap balance in the Antarctic. Figure 2.10 illustrates the sea level rise projected by GCMs for each of the six SRES scenarios up to 2100. The degree of sea level rise reflects the greenhouse gas emissions with more emissions leading to more sea level rise. By 2100, the full range of SRES scenarios suggests average sea level will increase by 8 to 88 cm. Again, the expected range is smaller at 30 to 50 cm. As with temperatures, sea levels will rise during the remainder of the century even if greenhouse gas emissions are stabilised (Church and Gregory, 2001).

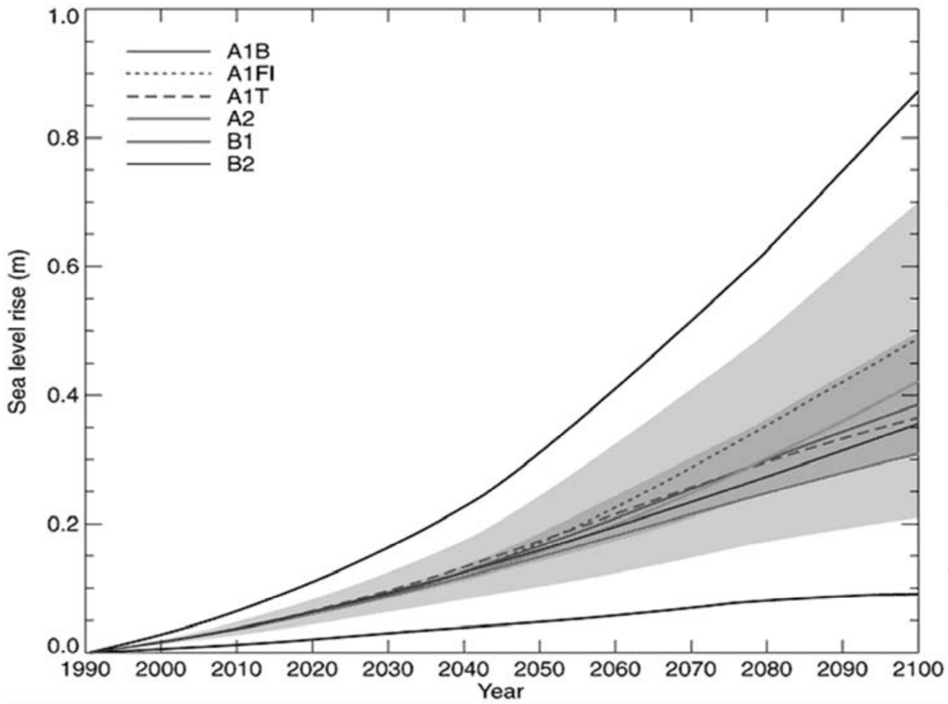

Figure 2.10: Global average sea-level rise from 1990-2100 from IPCC (Church J.A. Gregory J.M. 2001).

2.4.3 Potential Climate Impacts

Water Resources

Due to global warming, the availability of fresh water may lessen. Water is the most precious resource on the Earth although 70% of the surface is covered in it. Climate change will alter the availability of water: some places will face less rainfall especially during the summer months while increased temperature implies increased evaporation.

The process of transpiration through which plants take up water from the soil has a large impact on water resources. It is estimated that a doubling of atmospheric CO_2 and reduction in transpiration water loss from plants will result in more soil-water saturation and increases in water surface runoff by as much as 60 to 85 percent (Hardy, 2004).

Water is critical for life and living standards: drinking, production of food, for industry, for household and for environmental activities. Human activities can significantly alter the availability of water, e.g. farmers require larger amounts of water in the summer and power plant needs water for cooling. There will be serious impacts for many aspects of water resources as rising temperature will increase evaporation. The impact on rainfall will vary between regions with some areas experiencing greater incidences of flooding (South East Asia) and others greater drought (Africa).

Agriculture and Food Security

The growing of crops and raising of animals are very important for humans especially farmers. Decisions about what crops to grow are very much associated with the distribution of temperature and rainfall and the incidence of extreme weather events such as droughts and floods. The impact of changing climate on food security is highly complex and strongly dependent on economic and social change. Detailed studies have found out that the effect of climate change on world food supply with appropriate adaptation would not be very great (Hardy, 2004).

Human Health

The environment has a direct effect on human health. Environmental factors such as air pollution, poor soil, diminished water supplies, or polluted water will bring many diseases and present danger to human health. An example of rising temperature is the incidence of malaria. Generally, mosquitoes are sensitive to changes in temperature and the transmission frequency may increase due to the effect of higher temperatures. Food poisoning risk is very much associated with warm weather as high temperatures usually favour micro-organisms or bacteria in food such as salmonella. Other direct effects of climate change on human health will be through heat stress. Extreme temperatures can lead to cardiovascular and respiratory problems.

Economic Impacts

Estimating the economic costs of climate change is challenging as it involves measuring the physical impacts in terms of their impacts on economic activity, human life and the environment (IPCC, 2007). The cost of impacts includes the cost of direct damage and that required to climate. The cost of climate change is estimated to be to be as much as $US 300 billion a year with loss of land as sea levels rise, damage to fishing stocks, agriculture and water supplies, annually accounting for between 1 and 2 percent of global gross domestic product (GDP) depending on geographical area, demographic, environmental and economic development (UNEP United Nations Environment Programme, 2007). The global water industry will be facing $47 billion a year in losses, agriculture and forestry could lose up to $42 billion, while damage to factories and power stations from rising sea levels and storm average will cost $1 billion and ecosystem losses, including mangrove swamps, coral reefs and coastal lagoons could over $70 billion annually by 2050 (UNEP United Nations Environment Programme, 2007).

Figure 2.11 illustrates the types of impacts that could be experienced as the world experiences greenhouse gas warming. Warming temperatures will result in a number of impacts to the economy as follows:

- Insufficient food as crop yields decline. If the temperature rises 4°C and above, it will have a serious effect on global food production.
- Melting glaciers will encourage flood risk due to sea level rise, which will lead to reduced quality and supply of clean water to the world’s population.
- Rises in carbon dioxide levels will have a huge effect on ecosystems, as they are very vulnerable; for example, a 2°C rise in temperature will cause them to weaken and eventually die.

- Increasing temperatures also could give rise to sudden shifts in weather patterns such as monsoon rains, which will also threaten the livelihoods of people.

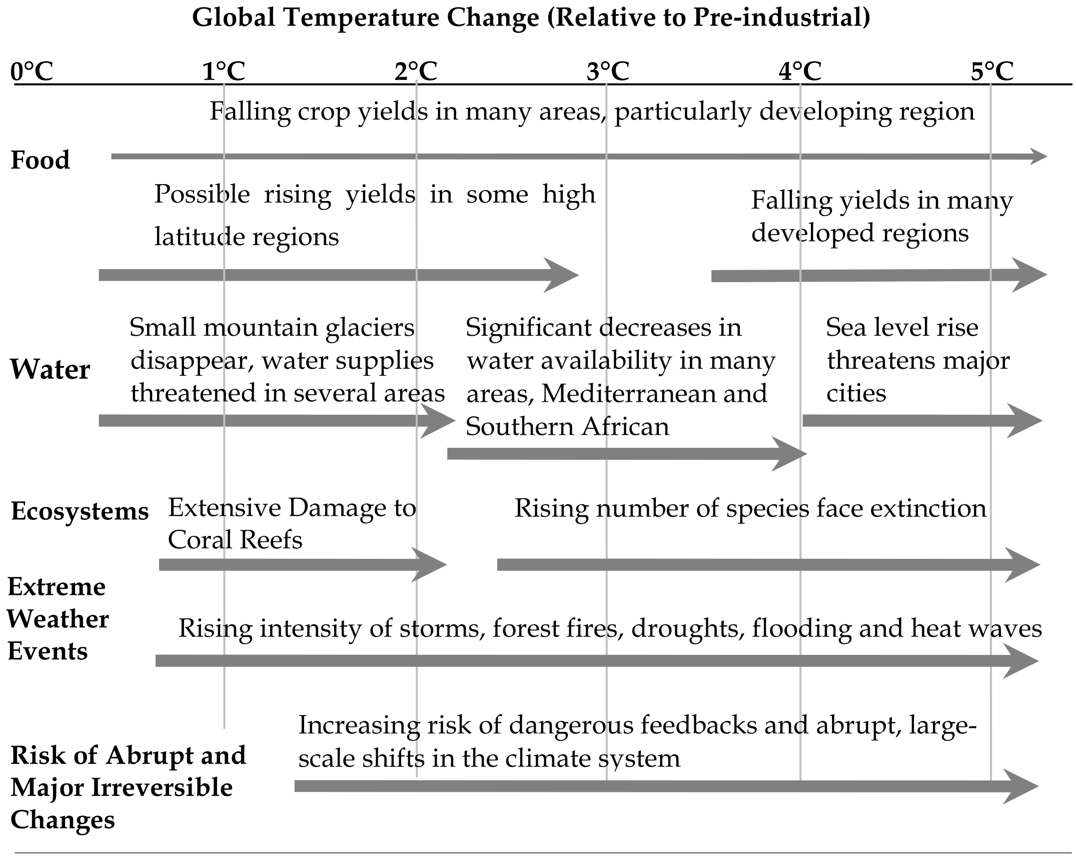

Figure 2.11: Probability ranges for temperature increases (IPCC, 2007).

2.5 Tackling Climate Change

The United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol provide a framework for international action on climate change. The Kyoto Protocol provides a collective commitment to reducing emissions although several of the largest polluting countries are not covered by emissions reduction targets (e.g., China, India) or have refused to ratify it (e.g. US, Australia). The six gases to be controlled are CO_2, CH_4, N_2O, HFCs, PFCs and SF_6. Tackling, the six gases together means that their overall climate effect can be reduced at a lower cost than tackling carbon dioxide on its own.

Modern economies rely on fossil fuel for energy. CO_2 emissions per head are associated with GDP per head. The evidence has shown that future emissions growth is coming from those countries with rapid population and GDP growth rates. Emissions are also correlated with income growth and the structure of economies. With strong, deliberate policy choices, it is possible to decarbonise both developed and developing economies on the scale required for climate stabilisation, while maintaining economic growth in both (IPCC, 2007).

2.6 Chapter Summary

This chapter reviews the basis for climate change and the projections for future concentrations of greenhouse gases. Projections of future climate are based on scenarios of greenhouse gas emissions primarily the SRES scenarios developed by the IPCC. Between 1990 and 2100, mean temperature is expected to rise by between 1.4 and 5.8°C which will have significant impacts on many areas of human activity.

Chapter 3

Climate and the Electricity Industry

Chapter two showed that the electricity industry has been a major contributor to CO_2 emissions and climate change through the burning of coal, oil and gas to produce electricity. However, the interaction between the electricity industry and climate is more complex than a simple cause-effect process as almost all aspects of the electricity industry are influenced by climate and potentially climate change. This chapter looks in detail at these influences and examines the potential impacts of changing climate on the generating sector, on transmission and distribution networks, and focuses in detail on electricity demand.

3.1 Impacts on Generation

Climate change will have a wide range of impacts on power generation of different types including thermal electric generation, hydropower, solar and wind power (Stern , 1998) and other renewables like marine (Harrison and Wallace, 2005).

3.1.1 Thermal Generation

In many countries thermal power stations are critical to electricity supply. For example in the UK, coal, gas and nuclear power stations make up 92% of UK installed capacity and supply 95% of electrical energy production (Department of Trade and Industry, 2006). They were responsible for 30% of the total CO_2 emissions in 2005 (Department of Trade and Industry, 2006). In developing nations, particularly China and India, thermal power plants powered by coal are being built in very large numbers: in China a 1000 MW coal plant is built every week. As such, thermal power plants will have a significant role in determining the extent of climate change in future. In turn, climate change will impact on thermal power stations through the need to minimise their emissions of CO_2 but also more directly on the efficiency and operation of power stations.

Efficiency

All thermal power stations are forms of heat engines. Heat engine performance is fundamentally driven by the temperature of the hot source and the cold sink to which heat is rejected. The Carnot efficiency is the maximum theoretically attainable efficiency (Eastop and McConkey, 1994) and depends on the difference between the maximum and minimum temperatures in the power cycle. The hottest temperature occurs when the fuel (coal, gas and oil) is burned or within the core of a nuclear reactor. The cold source is the water or air used for cooling and to which heat is rejected. It is the cold source which is affected directly by climate change as an increase in ambient temperature lowers the Carnot efficiency. With the temperature difference around 500°C, small increases in ambient temperature appear to only have a small impact on Carnot efficiency (UKCIRG, 1991). However, since real thermodynamic cycles are much less efficient, there is potential for power stations to show greater sensitivity to changes in ambient conditions driven by climate change (Harrison *et al.*, in preparation).

Higher temperatures not only decrease efficiency but also reduce the heat rate and output of power plants. Reductions in output may be caused by internal mechanical, material or operational constraints at high ambient temperatures (e.g. turbine back pressure or coal feed rate at coal plant). With higher temperature the density of air reduces which can reduce efficiency in air draft systems affecting the coal combustion processes of coal plant (Miller et al., 1992). Air density also affects the operation of Combined Cycle Gas Turbine (CCGT) stations. With gas turbines designed to operate with constant volumetric air flow rates, reduced density causes the mass flow to fall reducing the power of the gas turbine and the amount of heat generated in the heat recovery boiler (Kehlhofer et al., 1999). For example, a CCGT station rated at 500MW in the UK would be de-rated to 450MW for operation in the hot, dry, conditions experienced in the Middle East (UK Meteorological Office, 2006) while a 35°C variation in air temperature reduces CCGT power output by around 20% (Ponce et al., 2004). In evaporative cooling systems humidity plays a significant role in controlling cooling tower performance which in turn dictates the temperature of the water entering the condenser. Changes in humidity may also therefore affect power station efficiency (Miller et al., 1992).

Utilities with thermal power generation operation in the United States (US) were shown to be affected by a warmer climate in a 1987 study (Linder et al., 1987). Test data from south-eastern US generators were used to consider changes in plant heat rate and effective capacity that would result from seasonal temperature rises of around 1°C. This resulted in relatively small efficiency changes for a typical generator (0.22%). A more recent analysis for Finland (Tammelin et al., 2004) indicated that coal and nuclear power plants situated at the coast of the Baltic Sea would see reduced output in summer. Probable climate warming of 1.6-1.8°C during summer would mean that the water in the Baltic Sea would be 1-2°C higher resulting in 1% reduction in nuclear power plant production and about 0.25% reduction for coal-fired plant. In most cases the overall effect of global warming on thermal power efficiency is relatively small.

Cooling

Increases in high temperatures and humidity will also be detrimental to electricity generation from gas, oil, or nuclear steam cycles, which rely on cooling towers for the condensing process. Other potential impacts on thermal plant are related to the limits on intake or outlet temperature. Nuclear plant may face limits on intake temperature supplying essential auxiliary or emergency cooling systems (Miller et al., 1992). There are limits on heat discharge into water bodies to ensure water temperatures remain within limits that sustain the ecosystem. The temperature of the river downstream of the power plant is determined by the heat in the discharged coolant, the incident water temperature and flow of the river. The river temperature follows air temperatures so climate change will tend to raise background river water temperatures (Morrison et al., 2002). These effects may place restrictions on summer power generation at some river-based stations (Miller et al., 1992). This happened with French nuclear reactors in 1989 (United Kingdom climate Change Impacts Review Group, 1991) and again in 2003. In 2003 the combination of reduced cooling efficiency of thermal power plants and low river flows led to the complete shut down of six power plants; had the heatwave continued, as much as 30% of national power production would have been at risk (Létard et al., 2004).

The main risk is from lower river flows, although in serious droughts the abstraction rate for less water-demanding evaporative systems may exceed available flows or the river level may fall below the intake. The studies of the Tennessee Valley Authority (TVA) system by Miller *et al.* (Miller et al., 1992) found that in a hot dry year thermal compliance issues at nuclear and fossil stations reduced production by 2% under a uniform temperature rise of 4°F (2.2°C).

Flooding

Climate change will influence thermal plant located along rivers or coastal power stations. Problems include sea level rise threatening inundation of facilities, the potential for flooding due to storm surges as well as higher coastal erosion rates due to higher energy waves from storms and deeper water (United Kingdom Nirex Limited, 2005). There is some evidence that climate change will lead to an increase in cyclone activity and intensity and also monsoon intensity which could pose a threat to plant, particularly on the coast. With sea level projected to rise by up to 86 cm by 2080 it was identified that several nuclear sites were in danger of flooding over the next 100 years (United Kingdom Nirex Limited, 2005).

3.1.2 Hydropower

Hydropower is the major renewable energy source at the moment and installed capacity is expected to increase over the twenty first century (Nakicenovic et al., 1998). In addition to rising temperatures, global warming is expected to lead to increases in global precipitation levels of around 15% (Lal et al., 2001; Arnell, 1996). However, the changes will be different across regions with many areas of the world, particularly Africa, expected to see reduced rainfall. Changes in precipitation patterns will alter the timing and scale of river flows and significant change will impact hydropower generation. Hydroelectric schemes are designed for a particular river flow distribution so plant operation may become non-optimal under altered flow conditions.

In river basins which have snow-fall, higher temperatures will increase the proportion of rain, increasing winter river flows and reducing summer low flows (Gleick, 1986). Figure 3.1 shows river flows under current and potential climate change conditions for the Zambezi River upstream of Lake Kariba, Zimbabwe. The change in global temperature will increase evaporation levels and this effect is complicated by an increase in the moisture–holding capacity of air and other factors (e.g., wind speed). Whether changes in seasonal precipitation increase river runoff depends on regional climate and hydrology (Harrison and Whittington, 2001a). A temperature rise in the region of 2°C could change the evaporation by up to 40%, although this would be lower for an arid climate (Arnell and Reynard, 1993). Arnell (1996) drew several conclusions:

- Runoff is relatively more sensitive to precipitation change than temperature change.
- River basins tend to amplify changes in precipitation.

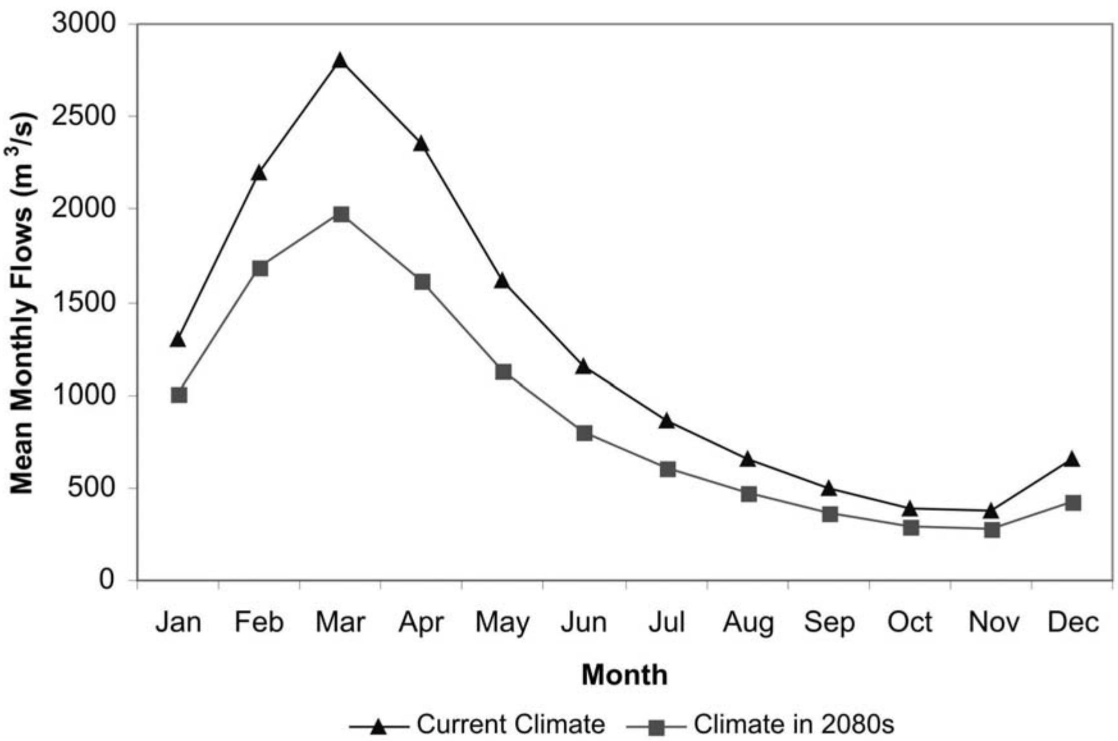

Figure 3.1: Runoff patterns under current and a potential climate change scenario for the Zambezi River (Harrison, 2001).

Hydropower has received the most attention in climate impact studies as it is the widest used renewable resource and is vulnerable to changes in several climatic variables. Reibsame et al. (1995) examined climate impacts in the Mekong delta (among other international rivers) under a range of potential GCM scenarios. Figure 3.2 shows the effect of a 5°C degree rise in mean annual temperature accompanied by a 4% rise in precipitation as simulated by the UK Hadley Centre GCM. In this case there are significant increases in several months. Other studies show reductions in flow and production. For example, Mimikou et al. (1995) found that for the Mesohora basin in Greece a 20% fall in precipitation, accompanied by a 4°C temperature increase would result in a 35% reduction in annual runoff.

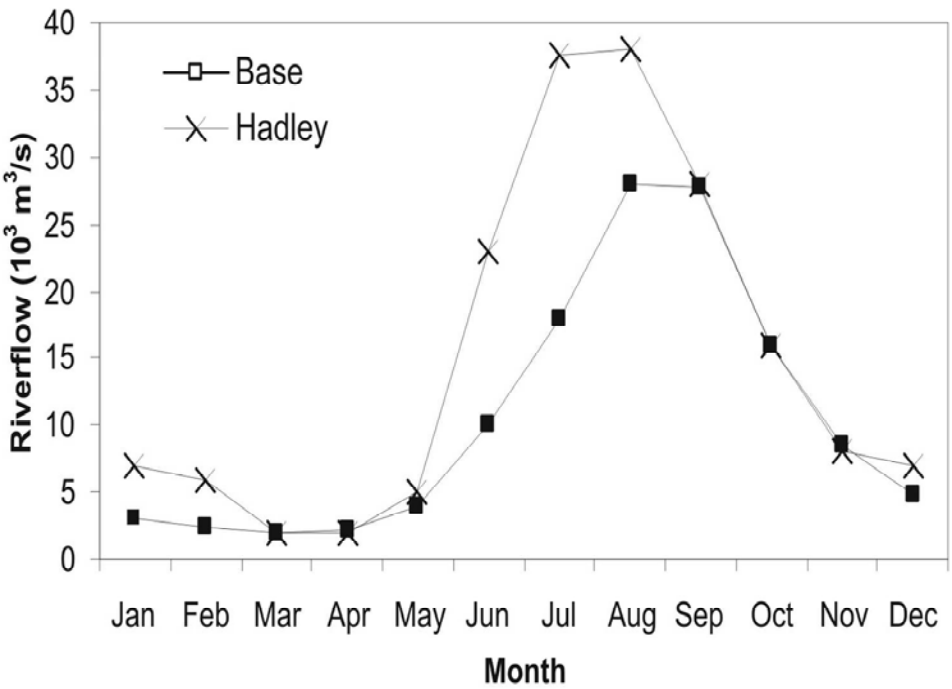

Figure 3.2: Historic (Base) and projected river flows at location in Lower Mekong Basin for Hadley Centre scenario (adapted from (Reibsame et al., 1995).

Table 3.1 shows a sample of potential impacts on hydropower production for several major rivers. Published results suggest the climate sensitivity of energy production is related to the storage available: in general, the greater the degree of storage, the lower the sensitivity (Harrison and Whittington, 2002). Where increases in flow are projected, the system's ability to harness the increased flows depends on whether sufficient turbine capacity or storage exists.

Changes in river flow and production will have an effect on income and will affect what has been termed 'willingness to develop' (Moreno and Skea, 1996), i.e. investment attraction. A series of studies (Harrison and Whittington, 2002; Harrison et al., 2003) for a planned hydropower scheme in Sub-Saharan Africa examined how climate change could affect the attractiveness of the scheme as an investment. The scheme's financial viability was shown to be sensitive to changes in rainfall and temperature.

River	Temperature (ºC)	Rainfall (%)	River Flows (%)	Production (%)
Nile (Reibsame et al. 1995)	+4.7	+22	-12	-21
Indus (Reibsame et al., 1995)	+2.0	+20	+19	+20
Colorado (Nash and Gleick, 1993)	+4.0	-20	-41	-49

Table 3.1: Example changes in annual hydro generation from changes in temperature.

3.1.3 Other Renewable Energy Sources

The potential implications of rising greenhouse gases and reducing fossil fuel resources have increased the interest in energy generated by renewable sources such as wind and solar power. Many countries have programmes to develop their wind, solar and other renewable resources. With most renewables 'driven' by the climate, they will be affected by climate change.

Wind Power

Wind power is the fastest growing renewable technology. For example, the UK's current installed wind capacity is of the order of 2GW but the potential is far greater

(BWEA, 2006) as the UK possesses the best onshore and offshore winds resources in Europe. By 2020 the UK Government and Scottish Executive have aspirations that renewables will meet 20% and 40% respectively of demand, with much of it coming from wind.

Wind turbines make use of the kinetic energy in moving air and their output is defined by the cubic relationship between power and wind speed (Manwell et al., 2002). The relationship indicates that for a given percentage change in wind speed, there will be a proportionately greater impact on the power output of a wind turbine. Baker et al. (1990) report that a 10% change in wind speed could change energy yields by 13 to 25%, depending on the site and season. A small but increasing number of studies, e.g. (Bogardi and Matyasovszky, 1996), have considered how wind power would be influenced by global warming.

A change in climate might modify the speed, direction and duration of speed wind in a specific area. Large-scale changes in climate will change wind characteristics as will storm frequency. Wind speed is clearly important given the cubic relationship with power but direction is also important as change in the prevailing wind direction may see the air passing over rougher terrain and will also impact on wake interaction between individual turbines in an array. The distribution of wind speed is an important indicator as wind turbines are designed to extract power from a specific range of speeds. Severe weather (thunderstorms, lightning, hail, icing, tornados, and hurricanes) can damage wind turbines (Jensen and Van Hulle, 1991). For example, Watson (2007) highlights the relationship between extreme winds and turbine failure rates. The impacts of climate change on wind power production are difficult to quantify as changes are extremely difficult to assess. Climate also affects turbine performance as the presence of salt spray, dust and ice can reduce production by about 8% (Lynette, 1989). Reduced icing would be expected in a warmer climate.

Solar Power

Solar power or photovoltaic (PV) power systems are dependent on local conditions (Radesovich and Skinrood, 1989). They are particularly sensitive to cloud cover as production can be reduced to as little as 5% under cloudy conditions and are also vulnerable to humidity haze (Kelly, 1993). Global changes in climate may alter cloud regimes, possibly leading to more or less direct solar radiation levels (Enquête, 1991). This will affect the production from PV systems. Cloudiness has recently increased over Europe, North America, India and Australia as a whole (IPCC, 1990a) but has decreased in Southern Australia and in the Sahel (CSIRO, 1992b).

Biomass Generation

Biomass power is the use of biomass in electricity generation. Biomass is plant matter from trees, grasses, crops and other biological materials. Biomass is estimated to account for 12-15% of global primary energy consumption (World Energy Council, 1993b). After oil, coal, and natural gas, biomass is the world’s most important source of energy. The supply of biomass fuels is available from various sources: forests, wood plantations, agricultural, industrial residues and even municipal solid wastes. 64% of biomass fuel comes from trees of which 88.5% is used as firewood and the rest as charcoal (Smith et al., 1993). Biomass is useful for developing countries (e.g. South East Asia, South America and Africa), where it accounts for 38% of consumption (Hall et al., 1993). It should be noted that not all biomass can be classed as renewable or sustainable as particularly in the developing world, many trees are cut for fuel but not replanted.

Biomass can be converted into electricity by undergoing two processes. The first stage is the supply process which is mainly related to the production, collection and the delivery of plant matter. The second stage in the process uses biomass to produce electricity. Biomass fuels are derived from four types of material such as: agricultural residues (e.g. straw from cereal production), agro-processing residues from crop processing, forestry residues (e.g. by product of timber and pulp production) and energy crops specifically to be used as fuel (EU, 2003). These four types can be used to generate electricity using various technologies.

Climate change will affect biomass as plant growth is strongly related to climate conditions. Higher concentrations of CO_2 may lead to increased plant growth but decreased rainfall may result in drought leading to lower plant growth or even plant death (Moreno and Skea, 1996).

Marine Energy

Wave and tidal energy is being developed seriously in the UK and Europe with devices on test and being deployed commercially. Harrison and Wallace (2005) have begun to examine the potential impact of changes in the wave regime on production and the economics of converters. Waves are created by wind activity and wave power is very sensitive to changes in wind speed. Tidal energy may also be affected by rising sea level which will change the shape and characteristics of sites currently suited to energy exploitation (Harrison et al., 2006).

3.2 Impact on Transmission and Distribution

Atmospheric conditions affect the power flow rating of transmission and distribution lines and are traditionally specified by national or international standards such as those published by the IEEE (Board, 1993). The thermal rating of a line is governed by the maximum conductor temperature allowed to avoid excessive sagging. The conductor temperature is influenced by the resistive heating effect but also ambient temperature, sunshine and wind speed, of which temperature has the major effect. Conductor capacity is often seasonal, with winter capacity in the UK being higher than in summer. For example, a typical 400 KV overhead line is rated at 2720 MVA for winter use but only 2190 MVA for summer (Wood, 2003). Higher temperatures will tend to reduce transmission capacity, worsening existing network constraints and necessitating load curtailment or expensive network upgrades.

Extreme weather events are problematic for transmission systems: high winds, heavy rain, high ice loads and lightning can all create faults, requiring more investment in the transmission system. The management of these requires investment (Wood, 2003). Extreme heat can cause overheating of transformers and cables but extremely cold conditions can also create problems. An ice storm in New England and South-Eastern Canada in January 1998 brought down transmission lines (Francis and Hengeveld, 1998) leaving three million people without electricity for almost a week. With an expectation of a greater frequency and intensity of extreme weather there is the potential for greater damage to the system and consequent supply interruptions.

3.3 Impacts on Electricity Demand

The most significant impact of climate change on the electricity industry may be on electricity demand. The potential impact of future changes in climate on electricity demand can be seen on a daily basis through the fluctuation of demand with weather conditions. Very significant changes in demand occur across the day as a result of peoples' activity but weather plays a significant role and introduces significant uncertainty. The need to precisely match electricity production with demand makes understanding and prediction of weather conditions critical for utilities. For example, the UK National Grid is sensitive to changes in weather: on a summer's day a shift from clear sky to thick cloud adds an additional 5% demand (2 GW) while wind adds an extra 0.7% (Wood, 2003). Such changes in demand require the scheduling of additional generation, potentially at short-notice. In liberalised systems such as the UK and USA, electricity suppliers must accurately predict weather conditions in order to manage their supply contacts. Where they fail to do this, they are exposed to significant imbalance penalties. These are some of the reasons why demand forecasting approaches have received lots of research attention e.g. (Lo and Wu, 2003) along with financial market techniques like weather derivatives.

Temperature changes and, to a lesser degree, wind speed, humidity, precipitation and cloud cover will influence future demand. Precipitation tends to cool the air as cooler rain effectively absorbs heat given its higher specific heat capacity. The evaporation that occurs after rain has fallen also has a cooling effect. Wind speed plays a role as it affects cooling by tending to draw warm air away from surfaces as well as affecting evaporation rates. Humidity affects rates of evaporation and high levels make cooling difficult. Cloud cover affects the strength of sunlight and alters heat gain.

Figure 3.3 shows the influence of climate on electricity demand. Demand is sensitive to climate as there are a wide range of uses for electricity that are climate and weather dependent:

- Space heating and cooling
- Refrigeration
- Water heating
- Water pumping

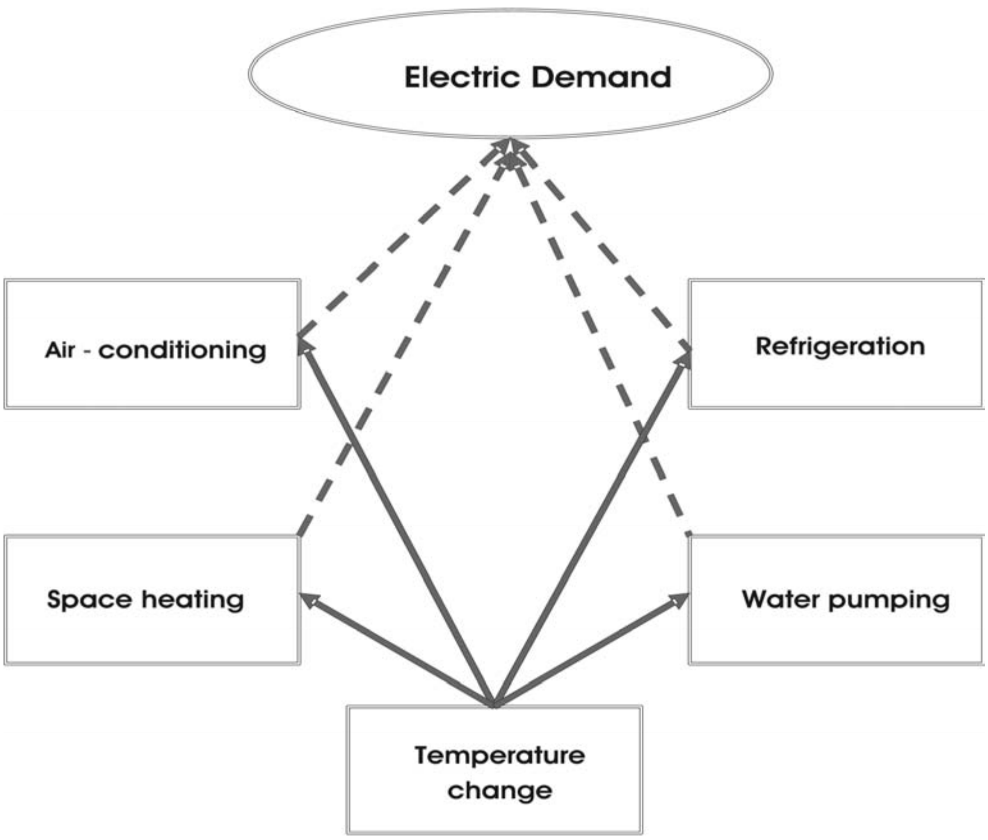

Figure 3.3: Electricity demand affected by temperature change.

3.3.1 Space heating and cooling

Air-conditioning and space heating requirements are likely to be changed by climate change. Warmer temperatures arising from climate change will tend to lower space heating requirements but raise those for space cooling. The extent of the impact on electricity demand will depend on the mix of resources used for heating and cooling. If air conditioning is produced using electricity but space heating is provided by gas boilers, then global warming will increase electricity demand but overall energy use could decrease (UKCCIRG, 1991).

Clearly the degree to which electricity demand in a given country might be sensitive to changes in climate will depend very much on its climate type and its level of economic development. High-latitude countries tend to have cool to cold winters and generally require heating. The requirement for space cooling will depend on how hot summer is: continental Europe may well require it but its cooler summers and infrequent hot days have in the past meant that widespread space cooling was not essential in the UK. Lower latitude countries like Thailand tend to have limited space heating requirements but significant cooling requirements to cope with temperatures of 30°C and above. Regions with high humidity coupled with high temperatures tend to require air-conditioning to cool and de-humidify the air.

The requirement for heating or cooling can be explained by human comfort. People do not like to be too hot or too cold and there is a band of temperatures which people in particular regions tend to be comfortable with. In Western Europe and North America this range is often around 15 to 20°C. In tropical Asia, the band would tend to be at a higher temperature. Should temperatures be below the comfortable range then heating is preferred, while above it there will be a preference for cooling (e.g. fan or air-conditioning).

Figure 3.4 shows these effects in the form of a V-shaped electricity consumption relationship with temperature (Jager, 1983). The amount of electricity demand used at the balance point temperature is the non-weather sensitive electricity consumption.

These characteristics are captured well with two measures: Cooling Degree Days (CDD) and Heating Degree Days (HDD). CDD is the amount by which daily mean temperature exceeds threshold temperature. HDD is the amount by which daily mean temperature is below the threshold temperature. HDD represents the heating being activated to increase indoor temperature to warm buildings.

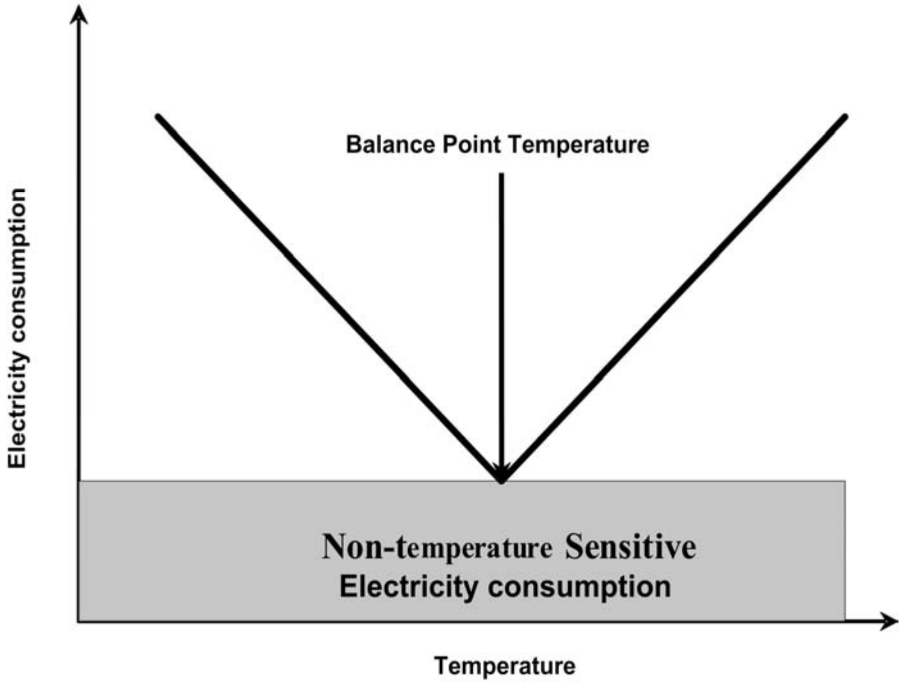

Figure 3.4: The relationship between demand consumption and temperature (Amato *et al.,* 2005).

Cooling degree-days (CDD) can be determined using the following expression:

$$CDD(T_d) = \begin{cases} \sum_{d=1}^{N} (T_b - T_d) & \text{for } T \geq T_b \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

Similarly, for heating degree-days (HDD):

$$HDD(T_d) = \begin{cases} \sum_{d=1}^{N} (T_d - T_b) & \text{for } T \le T_b \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

where T_d is the air temperature, T_b is the daily threshold temperature, and N is the number of days (d) in the period of interest. In Europe and America the threshold temperature is commonly around 15 to 20°C and in South East Asia the threshold temperature is 24°C. Degree days changes that push the daily temperature beyond the threshold will impact on electricity consumption under various climate change scenarios.

There is evidence to support growth in air-conditioning use. Several studies have shown that lower latitudes are using more energy for space cooling: over the 1981-2001 period in the Southern United States the average annual electricity growth rate was 3.5% but in the Northeast the average annual electricity growth rate was only 1.6% (Hojjati et al., 2005). In part, this growth will be climatic but socio-economic and other factors also play a significant role in determining the need for heating and cooling.

Increasing income tends to make energy relatively less expensive and will make people less careful over bills. This means that where air-conditioning is installed people will be inclined to set a cooler temperature setting. In addition higher income makes it more likely that air-conditioning will be installed in the first place. Comfort levels play an important role in the fitting and use of air-conditioning (CIBSE, 2005). There may be greater change in air-conditioning use in temperate countries such as the UK as very hot weather has historically been less common. As people are not acclimatised they will tend to 'feel' the heat more than those in warmer climates. Age plays a significant role in personal comfort as the old are less able to control their temperatures and are more vulnerable to high temperatures. As such, aging populations such as those in the West will tend to use relatively more air-conditioning than those of working age.

The age and construction of buildings play a role in regulating internal temperatures in response to outdoor conditions. Buildings with a high thermal mass can store significant amounts of heat within the fabric of the building (CIBSE, 2005). These smooth the response of internal temperatures allowing buildings to remain cooler in summer and warmer in during winter. Insulation is also very important in keeping heat in winter and heat out during summer. The size of windows and orientation of buildings affects the amount of solar gain which heats the building from the sun. This is a useful effect in high latitudes as it makes buildings easier to heat but it makes it difficult to keep buildings cool in summer. This is why many buildings at lower latitudes have significant amounts of shading and smaller windows. Buildings that are well insulated with large thermal mass will be less likely to warm up excessively. Unfortunately in the UK, many commercial and domestic buildings have poor energy efficiency as they tend to have low to medium thermal mass and limited insulation (CIBSE, 2005). As such, current UK buildings may be relatively sensitive to changes in temperature. A significant amount of research is going on into finding complementary ways of improving thermal performance of buildings to reduce overall energy use and thermal and energy-use sensitivity to a warming climate.

3.3.2 Refrigeration and water heating

As temperatures rise, the load on refrigeration units will increase and that for water heating should decrease. The extent will depend on regional factors as with heating and cooling although the direct effects are likely to be significantly less than the effects on air conditioning. Refrigeration and water-heating equipment is often located in conditioned spaces and is not affected by outdoor temperature changes. Additionally, refrigeration equipment evaporator coil temperatures are lower than those of air conditioning equipment and water heaters operate significantly hotter than room temperatures, so the proportionate impact will be lower (UKCCIRG, 1991).

3.3.3 Water pumping

Water pumping could significantly increase if the global temperature rises as water use for irrigation, residential, commercial and municipal sectors is often related to it.

Should surface water availability reduce due to changing rainfall patterns, there will tend to be an extra increase in groundwater pumping requirements, increasing electricity demand.

3.3.4 System implications

The changes in demand for air-conditioning, space heating, refrigeration and water pumping loads will affect both peak and 24-hour demand. The peak loading is particularly important as on occasions of extreme temperatures, this is likely to stress electricity systems in meeting demand. Again, France in 2003 is a good example of conditions where extremely hot temperatures gave rise to a significant increase in air-conditioning load at the very time that output from nuclear stations was limited by cooling limitations (Létard et al., 2004). The need to meet the additional demand created by warmer temperatures will require additional generation and potentially network capacity. It will also require changes in operational practices.

For example, maintenance in UK power stations tends to occur in the summer when electricity demand and consequently electricity prices have traditionally been lower. As temperatures rise, summer demand will rise and winter demand will fall, making maintenance periods scheduling more difficult for generators and the system operator. For example, the extreme temperatures experienced during the July 2006 heat wave forced National Grid to issue a Notice of Inadequate Capacity to bring on additional generation as the sustained hot weather raised the normally low summer demand by 2GW at the same time as many generators were offline undergoing planned maintenance (Harrison et al., in preparation).

3.3.5 Existing climate impact assessments

A range of assessments have been performed to try and understand and quantify the impact of climate change on electricity demand. They cover a range of locations and use a variety of methods. There is a steady change in method over time from simple uniform changes in temperature to the use of results from GCMs. This section documents them based on their country or region and their details and findings are summarised in Table 3.2.

North America

An early and extensive study was by Linder et al. in 1987. It focussed on changes in demand and consequent impacts on generation needs in the United States (Linder, 1987) for sample utilities in New York State (NY) and the Southeast (SE) of the country. The study identified changes in both peak and overall electricity demand. With the relatively low temperature rise expected by 2015 (0.8-1.0°C) overall electricity demand would rise by 0.45% for New York and by 3.4% for the SE. Peak demand would rise by 3.3% and 7.0% for NY and SE, respectively. The larger increases experienced by the SE utility are due partly to higher expected temperatures but mostly due to a relatively greater sensitivity to temperature changes given the more extensive reliance on air-conditioning. These were estimated at 4.0%/°C for NY and 6.8%/°C for the SE. The knock on effect on generation resulting from the temperature rise was significant with up to 1430 MW more capacity required in NY and 1420 MW in the SE. Overall, extra US demand of around 14% to 23% was expected between 2010 and 2050 (Linder, 1990: Linder et al., 1987).

More up to date studies for the USA include those by Belzer et al. (1996) and Ruth and Lin (2005) investigated changes in commercial energy use due to climate change and found that a 4°C increase in average annual temperature will result in up to a to 5% reduction by 2030 (Belzer et al., 1996). Ruth and Lin (2005) for Maryland, use degree days to show that electricity consumption for cooling may increase by 10.3% while that for heating may decrease by 6.5% (Ruth and Lin, 2005.). The US National Weather Station at the National Oceanic and Atmospheric Administration (NWSNOAA, 2001) forecast changes in heating and cooling degree days. Considerable increases in summer CDD are up to 19% by the 2020s and 44% by the 2050s. During the winter months heating degree days reduces by 10% and 21% in the 2020s and 2050s respectively.

The work by Amato and Pavlova (2005) suggests that by 2030 climate change may account for up to 40% of increases in energy demand in Massachusetts (Amato et Al., 2005). Sailor et al. (2001) showed significant variation in demand sensitivities and found that the increase in residential per capita electricity use was 11.6% higher due to a change in temperature of 2°C. In Canada, climate change will incur a 2.1% increase in per capita residential electricity demand consumption by 2020 (New England Regional Assessment Group, 2001).

UK

The potential for changes in UK energy and electricity demand was identified by the UK Climate Impacts Review Group in 1991 report (UKCCIRG, 1991). A mixture of top-down and bottom-up models were applied to estimate changes in across demand sectors and fuel types. By 2030 they estimated that household energy demand would rise by 5 to 16% and by 7 to 22% by 2050. Primarily due to space heating changes gas demand could increase by 6 to 14% by 2030 and 10-20% by 2050. Electricity changes would be smaller at around 3 to 7% and 2 to 4% on the same timescales. There have been significant climate modelling improvements since the early 1990s which suggest potentially larger changes.

More recent analysis by Hulme et al. (2002) was based on regional climate modelling of the UK for the UK Climate Impacts Programme (Hulme et al., 2002). It suggests significant changes in heating and cooling degree days although these were not translated into energy changes: warming would lower HDDs by up to 15% by the 2020s and 15–45% by the 2080s and there would be potentially larger increases in cooling by 2080 with CDD in southern England increasing by 30–90% and doubling in colder Scotland.

A very recent and more sophisticated analysis by Hor and Watson (2007) modelled electricity demand using a time-series regression approach. Application of the UKCIP climate change scenarios suggests significant shifts in UK daily and seasonal load patterns. As shown in Figure 3.5, summer peak loads currently occur around midday but are lower than all other seasons (around 13% below winter demand at this time of day). Under the UKCIP02 High Emissions scenario the midday gap reduces progressively: by the 2020s the winter-summer gap is down to 8.5% and is only 2.5% by the 2050s. By the 2080s (Figure 3.6), summer midday demand exceeds all other seasons and is 12.5% above winter demand in this hour. It is noticeable that summer peak demand tends to get later in the day the further into the future we progress. Although overall peak demand remains during winter evenings, the changes in winter and summer load patterns are remarkable.

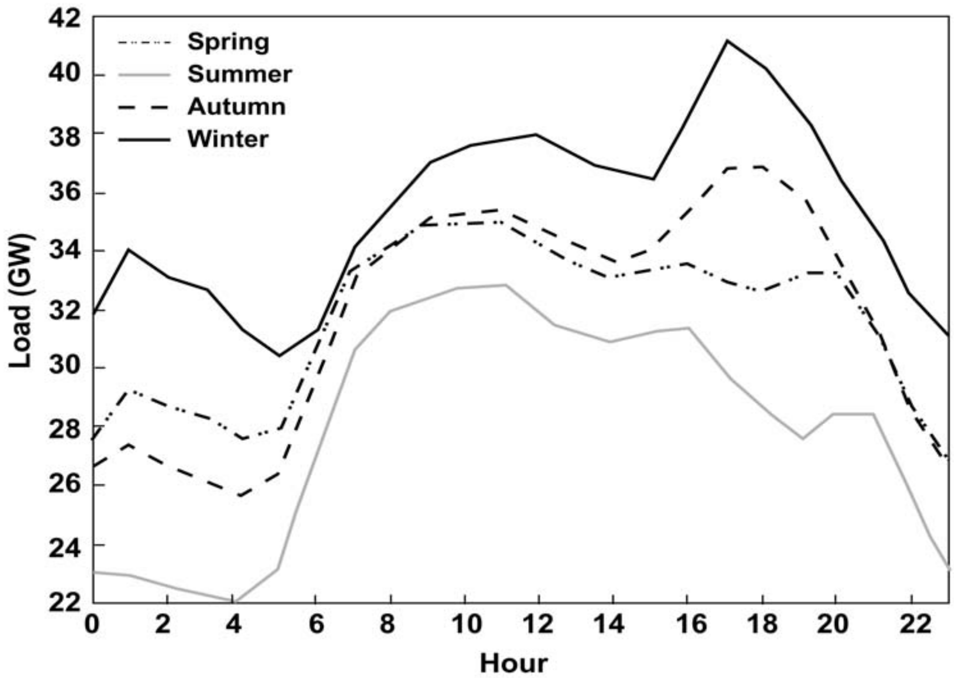

Figure 3.5: Current UK daily demand patterns (Hor and Watson, 2007).

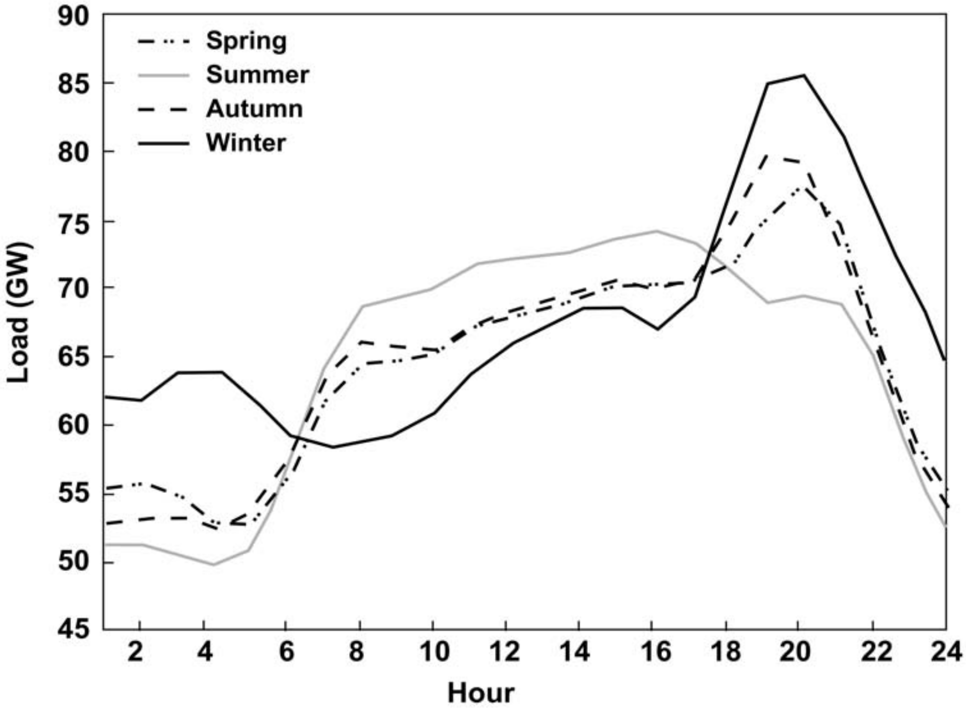

Figure 3.6: Projected UK daily demand patterns in 2080s under UKCIP02 High Emissions scenario (Hor and Watson, 2007).

Europe

A change in Finnish building heating demand was identified by Venäläinen et al. (2004). The average increase in temperature over land is expected to be about 2°C in the year 2030s. The study found that reductions in heating demand by up to 4% could be expected by 2020 with larger, reductions of 14% and 25%, by 2050 and 2100, respectively.

The impact of climate warming on Swiss building energy demand was investigated by means of the degree-day method. Christenson et al., (2005) apply the process to estimate CDD from monthly temperature changes to test Swiss locations. Using the degree-days method with typical temperature threshold values for heating of 8, 10 and 12°C, Switzerland's current buildings would show a significant reduction in heating demand of between 11% and 18% over the period 1901-2003. As regards cooling energy demand, a significant increase in cooling potential was found between 1901 and 2003 of between 50% and 170% on CDD(Christenson et al., 2005).

Several studies have considered Greece. Cartalis and Synodinou (2001) apply the ESCAPE model to modelling seasonal HDD and CDD changes in 2030 for a series of scenarios. Under a business as usual scenario around a 1°C increases in temperature would occur across the year. This change would decrease the heating demand by 10% but will increase the energy used for air-conditioning cooling by over 28%. (Cartalis and Synodinou, 2001) Another study of mainland Greece by Mirasgedis et al. (2007). used a regression method driven by OECD socio-economic projections and a version of the HadCM3 model. For one scenario the annual temperature for Athens is projected to increase by 4.8 °C by the 2080s, but with July (summer) averages projected to increase by 7.5 °C (relative to 1961 to 1990). The monthly degree day calculations suggest mean annual electricity demand could rise by 3.6 to 5.5% and summer mean demand would increase by 13%.

Segal et al., (1992) provide estimates for the sensitivity of summer peak demand in Israel. Using a series of linear regressions between peak hourly demand and a range of meteorological predictors, it was estimated that an increase in temperature 0.75°C to 4°C would drive a 2.7% to 10.9% increase in average summer peak electric loads (Segal et al., 1992).

Rest of the World

Jollands et al. (2006) applied climate scenarios to model seasonal HDD change in New Zealand. Four scenarios (from CSIRO and Hadley GCMs) project temperature increases by 2030 of 0.23-0.82°C in summer, 0.24-1.03°C in autumn, 0.34-0.87°C in winter and 0.29-0.65°C in spring. As a result, electricity consumption could reduce by up to 0.77% (Jollands et al., 2006).

Thatcher (2007) describes demand models for four different Australian states. The CSIRO Mk3 GCM global climate model projected differences in the average maximum temperature between 2001-2010 and 2051-2060 data sets were applied for the states of New South Wales (NSW), Victoria (VIC), Queensland (QLD) and South Australia (SA). The increases were 0.9, 1.2, 1.2 and 1.1°C, respectively. The increases were applied to the electricity demand models predicting changes in peak regional demand of -2.1 ± 1.0% for NSW, -0.1 ± 0.7% for VIC, +1.1 ± 1.4% for QLD and +4.5 ± 2.7% for SA (Thatcher, 2007).

Reference	**Location**	**Model**	**Future period**	**Temp. scenario**	**Temp change**	**Demand change**
Amato et al. (2005)	(USA)	Degree days	2020	HadCM2 CCC	N/A	+2.1%
Cartalis et al. (2001)	Greece	Degree days	2030	ESCAPE multi GCM	+1°C	HDD 10%; CDD +28%
Christenson et al. (2005)	Switzerla nd	Degree days	1901-2003	GCM	1-3°C	HDD 11-18% CDD 50-170%
Jollands et al. (2006)	New Zealand	Degree days	2005	CSIRO, Hadley	0.23-1.03°C	-0.77%
Linder et al. (1987 and 1990)	New York (US)	Degree days	1984-1995, 1995-2015	GCM	0.8-1°C	annual 1.58-1.56%
Mirasgedis et al. (2007)	Greece	Degree days	2080	HadCM3	+4.8°C	+3.3-5.5%
Ruth et al. (2005)	Maryland (US)	Degree days	1960-2030	HadCM2	+2°C	10%
Segal et al. (1992)	Israel	Degree days	1988	Hypothetic al	+4°C	+2.7-10%
Thatcher (2007)	Australia	Degree days	2050s	CSIRO, GCM	+1 to +7°C	±1.0-±2.7%
Venäläinen et al.(2004)	Finland	Degree days	1991-2100	HadCM3	+2°C	HDD: -25%

Table 3.2: Summary of studies investigating climate impacts on electricity demand.

Implications

Increases in electricity demand and potentially reductions in supply may lead to greater investment requirements in generation and transmission infrastructure. The 14 to 23% growth in US peak demand by 2050 was estimated to require additional investments of $200-300 billion (Linder, 1990). Rosenthal et al. (1995) estimate that a 1°C warming in the US will reduce energy spending by $5.5 billion and primary energy use by 0.70% in 2010 relative to a non-warming scenario (Rosenthal et al., 1995). If the temperature rises by 2°C the US energy spending will rise by $6 billion in 2060 (Morrison, 1998). Tol (2002a, 2002b) estimated the effects of climate change on the demand for global energy, extrapolating from a simple United Kingdom model that relates the energy used for heating or cooling to degree days, per capita income, and energy efficiency. According to Tol (2002a, 2002b), by 2100 the benefit of reduced heating will be about 0.75% of gross domestic product (GDP) and damage in the form of increased cooling will be approximately 0.45%.

3.4 Research Needs

Existing assessment of climate change impacts on the electricity industry suggest that the impact on demand is likely to be the most significant. As illustrated here there are a number of demand studies published over the last 20 years for a range of different countries. However as Moreno and Skea (1995) point out these are mainly in developed nations in North America, Europe and Australasia. There has been little or no analysis of developing nations. Developing nations, like Thailand and others in South East Asia, are the most rapidly developing. In doing so their electricity demand is also increasing rapidly. The potential for increases in electricity demand has several dangers for such developing nations:

- supplying electricity requires lots of money to finance capital projects like power plants and networks: increased demand will increase the amount of wealth devoted to this;
- power shortages caused by growth in power demand exceeding supply has significant economic impacts which the countries cannot afford;

- with most power generation coming from fossil fuel sources, extra demand suggests extra fuel costs, CO_2 emissions and greater climate change.

These effects highlight the need to examine the impact of rising temperatures on a developing nation like Thailand.

3.5 Chapter Summary

This chapter details the potential impact of climate change on the electricity sector. It considers electricity generation, transmission and distribution but focuses on electricity demand. It discusses the mechanisms through which higher air temperature will influence electricity consumption and provides an extensive summary of existing knowledge and case studies in this field. It highlighted that there were few (if any) studies in developing nations which underlines the benefit of assessing a country like Thailand.

Chapter 4

Electricity Demand in Thailand

To examine the impact of a changing climate on Thailand's electricity demand it is important to understand the nature of the Thai electricity sector, the patterns of electricity use across a range of time scales and the potential approaches to modelling electricity demand. This chapter begins by describing the make up of the Thai electricity industry before discussing the characteristics of demand.

4.1 Thailand's Electricity Industry

The Electricity Generating Authority of Thailand (EGAT) is a state enterprise which was established in 1969 to unify the functions and responsibilities of three independent state enterprises: the Yanhee Electricity Authority (YEA), Lignite Authority (LA) and the Northeast Electricity Authority (NEA). EGAT is allowed to establish subsidiary companies to undertake businesses relating to electric energy and other businesses which are related to the operation of EGAT. The scope of activities is extended to collaboration with other organisations within the private or public sectors. EGAT's key policy is to generate and transmit sufficient power to every client at reasonable prices and maintain a power system with high reliability and stability.

EGAT is responsible for generation, acquisition, and transmission of electricity to the two distribution authorities, the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA). EGAT has also been authorised to sell bulk power to other power utilities in neighbouring countries as shown in Figure 4.1 (EGAT 2003)

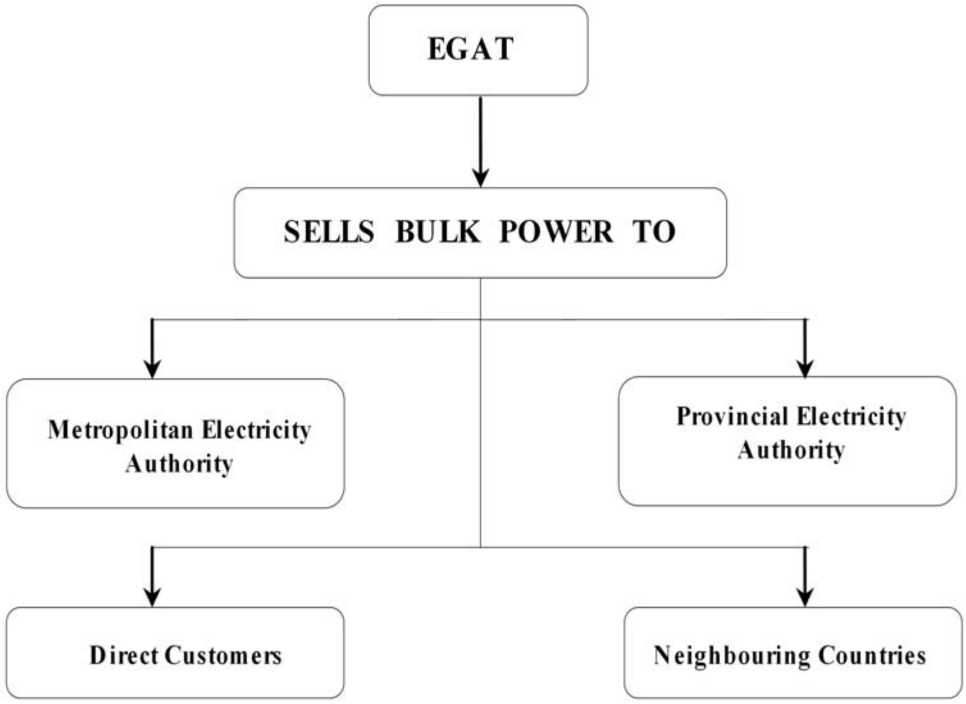

Figure 4.1: Power utilities in Thailand (EPPO, January 2004).

4.1.1 Responsibilities

Electricity generation and supply is presently managed by the three power utilities EGAT, MEA and PEA. EGAT is responsible for generation and is under the control of the Office of the Prime Minister while MEA and PEA are both attached to the Ministry of Interior. Policy on energy planning, management and utilization at the national level is under the responsibility of the Energy Policy and Planning Office (EPPO). It has as its members Ministers from related Ministries and Chiefs of Concerned Government agencies. It submits national energy policies and energy management and development plans to the Cabinet and EPPO is responsible for managing the oil fund and for formulating policies and measures related to oil prices. Finally, EPPO recommends and organises tasks relating to energy conservation and promote production and use of renewable energy.

EGAT is responsible for the generation, transmission and survey of power plant locations, line route design, operation and maintenance of the generation and transmission system. The MEA and PEA have a similar role for the distribution systems. EGAT carries on the development planning for a period of 12 to 15 years into the future according to the condition of the country's economy and energy demand growth. The huge investment in power system expansion required is so large that the Government alone is no longer able to provide it all.

EGAT's responsibility is for the planning of fuel utilization for power generation in order to keep energy cost at a low price at all times. The transmission of the power to MEA, PEA and direct customers must be efficiently managed so that the stability, safety and standard of power supply can be ensured while the production cost is at a reasonable rate. The aim of EGAT is serving customer demand which requires the development and expansion of the generation and transmission systems without any intervention on patterns of customer electricity utilization. In order to reduce the level of investment by EGAT, MEA and PEA, it has become necessary to introduce demand side management to reduce consumption and to provide incentives for efficient use of electricity and, in the long run, to lower energy cost.

As electricity is still regarded as a form of public supply, the Government controls electricity tariffs. The tariff structure must be approved by EPPO and the Cabinet who base their decision on supporting information provided by a Working Group consisting of representatives from various organisations including EGAT.

4.1.2 ESI Reform

The Thai electricity industry has been undergoing market reform. EGAT currently acts as the single-buyer, purchasing all power from independent power producers (IPPs), small power producers (SPPs) and its own thermal and hydro generators. There is no competition in wholesale electricity as MEA and PEA cannot choose to purchase from any generators or suppliers other than EGAT. Figure 4.2 shows the monopoly structure of the industry which lacks competition in operation and investments. The key attributes and issues associated with the Thai industry are:

- Limited private sector participation in generation providing for a portion of the capital needs of EGAT,
- Long-term central power planning under EGAT's responsibility,
- Limited accountability or incentives to gain productivity efficiencies, due to a lack of competition between generators,
- Commercial risk is shared by the private sector and the government-owned entities,
- No customer access to competitive power, except through SPPs, and
- Approval for an independent regulatory regime for electricity.

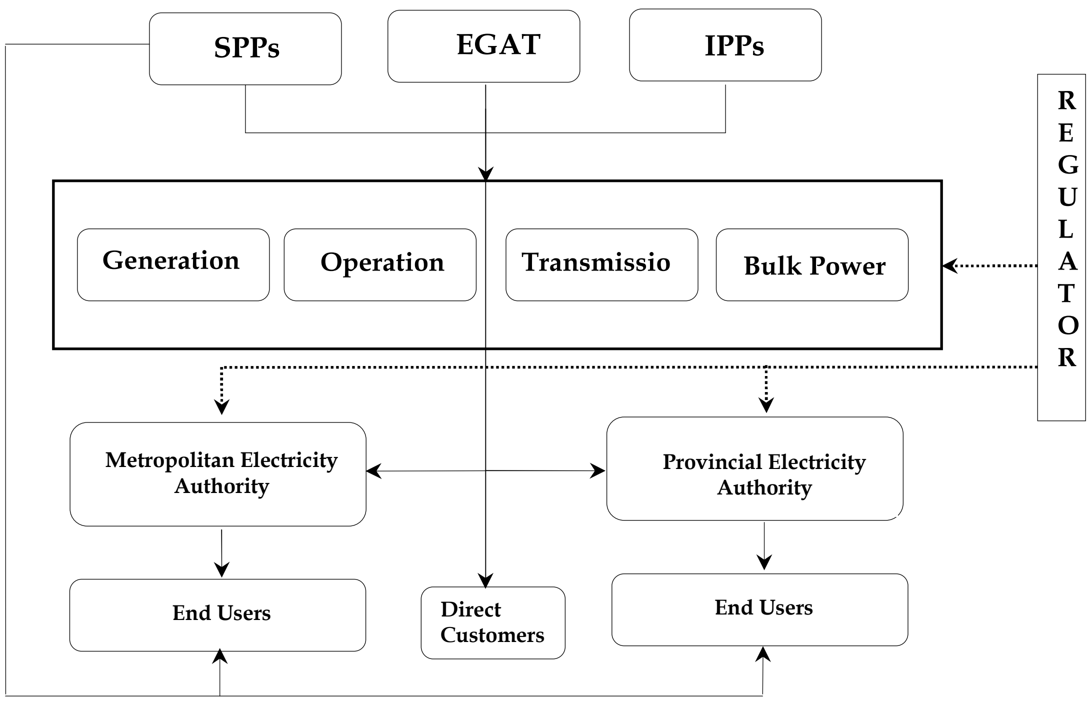

Figure 4.2: Power utilities Thai ESI structure (EPPO January 2004).

4.1.3 Role of Energy Resources

The Government of Thailand has pledged support for the joint exploitation of energy resources (e.g., natural gas, lignite and hydroelectric power) with private companies in Thailand and neighbouring counties. There is currently private sector input in the form of IPPs, SPPs, the electricity generating company (EGCO), and Ratchaburi. Each is described in further detail below.

Independent Power Producers: EGAT issued the first proposal for power purchase from IPPs and has signed power purchase agreements with several IPPs, accounting for 5944MW of total generating capacity.

Small Power Producers: SPPs include renewable generation technologies and generation. The maximum capacity to be sold by an SPP to EGAT is not to exceed 90MW, but SPPs can sell directly to large industrial customers.

Electricity Generating Company (EGCO): EGCO was formed in 1992 and purchased the 4×300MW Rayong CCGT station from EGAT. EGCO subsequently purchased 2×27MW thermal and 600MW CCGT stations.

Ratchaburi: Ratchaburi was formed in 1996 when EGAT's thermal power plants were to be privatised. The plans attracted opposition from the EGAT employee association in 1997/1998, and finally an agreement was reached to privatise Ratchaburi first, as it would have no impact on employees. An initial public offering of shares of the company was issued in 2000. EGAT purchased 60% of the shares and the general public purchased the remaining 40% of shares.

Neighbouring Countries: There are several agreements on power purchases and sales with neighbouring countries (EGAT 2003).

- Laos PDR: The Thai government agreed to purchase hydro electricity of up to 3000MW.

- China: Thailand has agreed to purchase the electricity power export of 3000MW by the end of 2017.
- Myanmar: The government of Thailand and Union of Myanmar entered into a Memorandum of Understanding (MOU) to buy up to 1500MW by 2010.
- Cambodia: Initially, Thailand will sell 20 to 30MW of capacity to Cambodia.

4.1.4 Thai Generating Capacity

As of April 2003, the total generating capacity is 18121MW of which 2000MW is from hydro; 5000MW from thermal power plants, 3200MW from CCGT, 321MW from peaking plants and 7600MW purchased from IPPs, SPPs, and neighbouring countries (EGAT 2003). In 2004 70% of non EGAT generated power was purchased from IPPs and SPPs in Thailand and 30% was from neighbouring countries (Laos PDR and Malaysia). Figure 4.3 shows recent and forecast generating capacity.

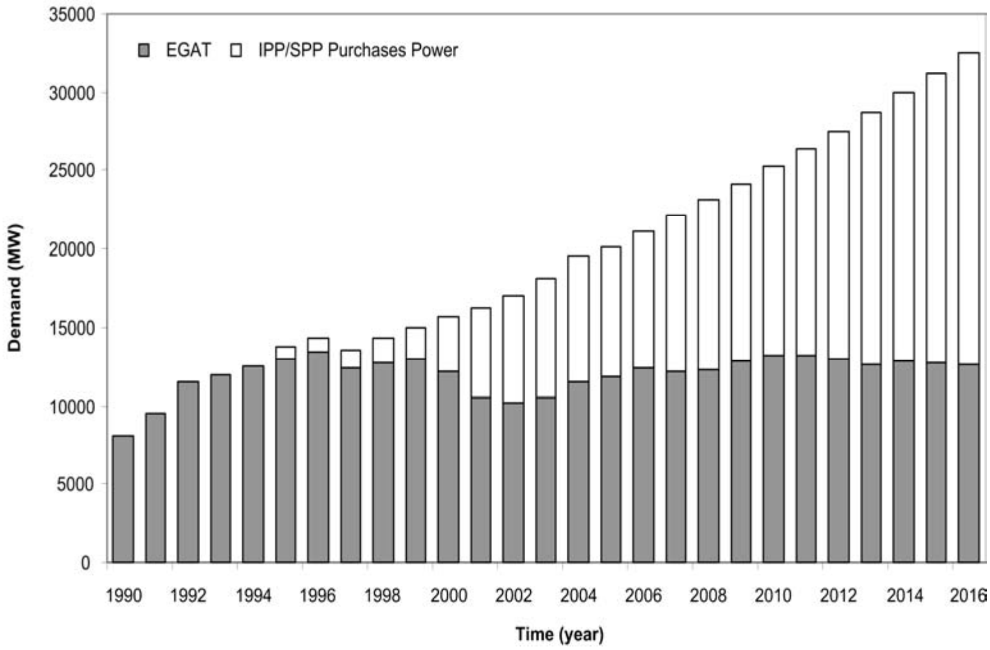

Figure 4.3: The past and future trend of generation capacity in Thailand (EGAT 2004).

4.2 The Characteristics of Thai Electricity Demand

4.2.1 Long term demand patterns

Thailand's electricity demand has grown significantly over recent decades. Between 1981 and 2000 annual electricity demand in Thailand grew by more than 8.6% per year, and annual energy demand grew by 7.5% per year while the economy expanded at 6.1% per year (Ussanarassamee and Bhattacharyya, 2005). From the Thai economic crisis in 1998 until now, the Thai economy has grown from 4.0% to 6.0% annually (Fiscal Policy Office Ministry of Finance, 2004). Figure 4.4 shows the annual electricity demand from 1960 to 2005.

Table 4.1 takes a closer look at more recent years from 1997 to 2004. Although mostly these show significant annual growth there are specific instances where peak demand and overall energy consumption fell. This occurred in 1998 and 1999 following the economic crisis that struck Thailand in 1997 following the devaluation of the Thai Baht.

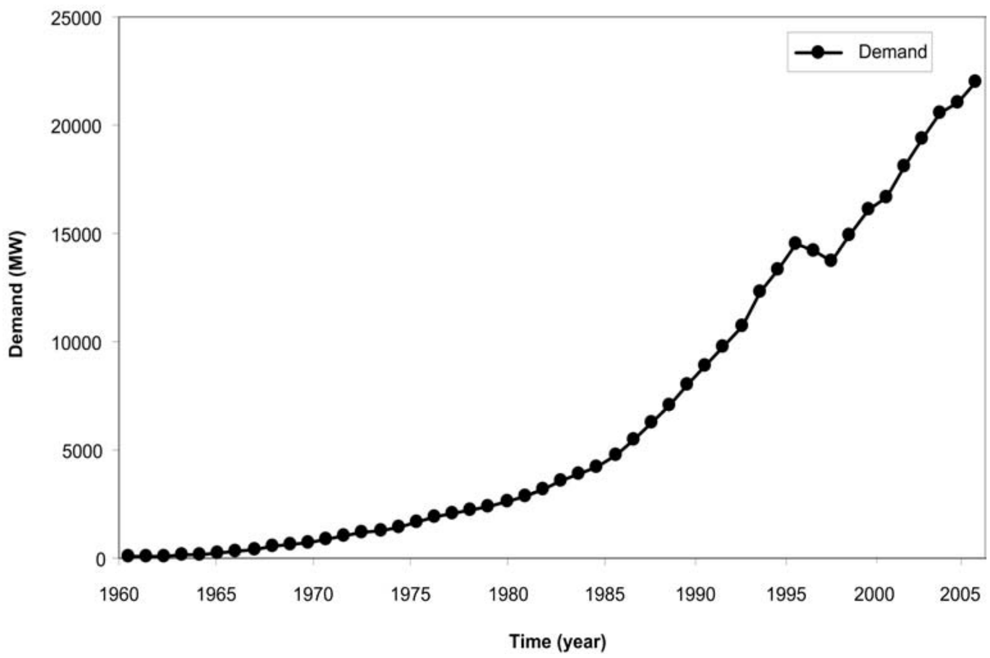

Figure 4.4: Growth in electricity demand in Thailand (1960-2005).

Year	Annual peak demand			Annual energy consumption		
	MW	Increase		GWh	Increase	
		MW	%		GWh	%
1997	14506	1195	8.9	93408	5626	6.4
1998	14179	-326	-2.3	91153	-2254	-2.4
1999	13712	-467	-3.3	91431	278	0.3
2000	14918	1205	8.8	98536	7105	7.7
2001	16126	1208	4.1	103868	5331	5.4
2002	16681	554	3.4	111299	7431	7.2
2003	18121	1440	8.6	118374	7074	6.36
2004	19600	1478	8.2	126811	8436	7.1

Table 4.1: Historic demand (peak power and energy) in Thailand, 1997-2016 (EGAT, 2004).

In the long term Thai electricity demand is being driven by a complex range of socio-economic and technical factors. Among the most significant include economic activity, population and demographic factors. Growth in economic activity tends to raise electricity demand. It is well correlated with Gross Domestic Product (GDP) which measures the value of goods and services within a country. Increased economic activity implies greater electricity demand, partially due to higher investment and consumption in domestic, industrial and commercial activities. Population trends also play a major role as a larger population will use more electricity. This is particularly true if the demographics suggest an increase in the number of households. Households are important because equipment and associated energy use (e.g., air-conditioning and refrigeration) increases with the number of households. Although greater economic activity tends to raise electricity consumption, it is also the case that the availability of electricity raises and sustains economic activity. This is because modern manufacturing and commercial activities rely on secure electricity supplies. Shortages in electricity are one of the main restrictions on the growth in living standards in developing nations.

The correlation between growth in GDP and electricity demand in Thailand was calculated from data for 1994-2004 from the Ministry of Finance (Ministry of Finance 2003-2004; EGAT, 2004). With a correlation coefficient of 0.77 there is good agreement between them. Figure 4.5 shows the relationship between per capita GDP and electricity consumption in Thailand. Electricity demand tends to closely follow trends in economic activity. There is significant annual growth prior to and following the sharp decline in GDP during the 1997 economic crisis. There is an apparent lag in the response of electricity demand following the initial fall in GDP and the reductions in electricity demand are less severe and long lasting than the driving reduction in GDP.

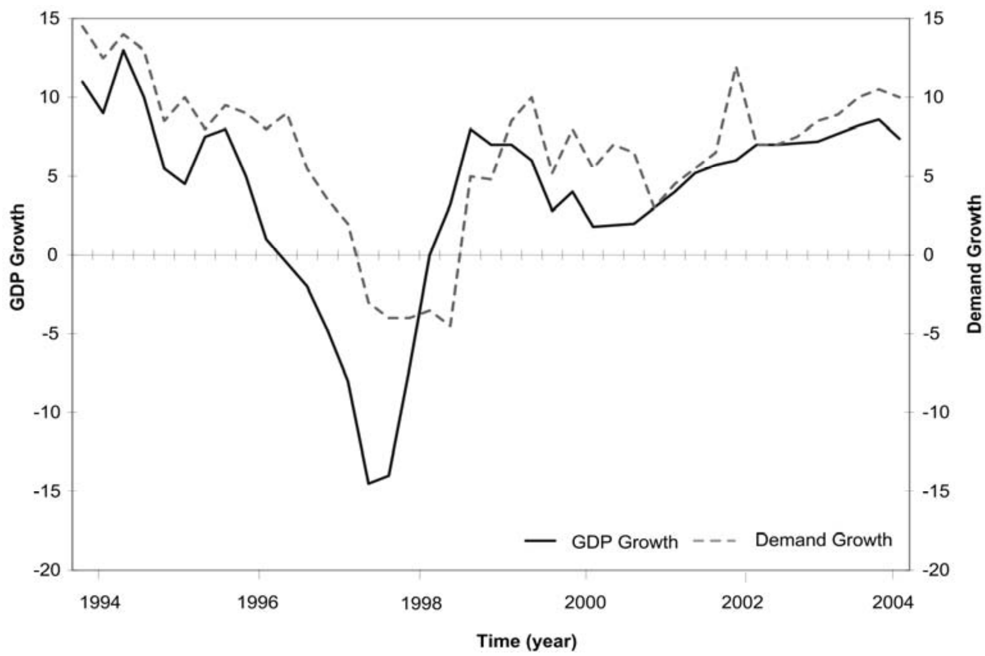

Figure 4.5: Annual GDP and demand growth rate in Thailand, 1994 - 2004.

Comparison with other Asian Economies

Thailand is one of a series of countries in Asia that have rapidly growing economies and electricity sectors. Asia's population is 2.75 billion or 45% of the World's population. Table 4.2 shows these figures for the 10 fastest growing Asian economies in 2003 (Chen et al., 2006). China, India and Korea are the top countries for increasing CO_2 emission. In 2003, these 10 economies had a combined GDP of US$ 3,573 billion, electricity consumption of 3,174TWh and CO_2 emissions of 6,241 Mt CO_2.

Country	Population (million)	GDP (billion $)	Electricity Consumption (TWh)	CO_2 emission (million tonnes)
China	1288.4	1375.2	1776.1	3719.4
Hong Kong	6.82	174.7	38.5	40.5
India	1064.4	543.7	463.3	1049.7
Indonesia	214.7	167.7	94.5	318.1
Korea	47.9	585.7	335.8	448.4
Malaysia	24.7	99.4	74.8	122.8
Philippines	81.5	85.3	46.1	70.5
Singapore	4.3	93.3	33.4	38.2
Taiwan	22.6	306.6	201.1	245.2
Thailand	62	141.1	110.6	188.4
Total	**2817.4**	**3572.7**	**3174.1**	**6241.1**

Table 4.2: Economic, electricity consumption and CO_2 emissions for the ten fastest growing Asian nations (International Energy Agency, 2005).

Thailand's economic and energy demand growth is fairly similar to other Asian nations. For example, in South Korea, economic growth (6.8%/year in real GDP) has boosted electricity consumption, increasing by 12% per year between 1970 and 2000 (Yoo, 2005). The Japanese annual growth in overall consumer electricity consumption from the past three decades is about 4.5% (Uchiyama, 2002). In China, annual economic growth rate is about 9.7% and average increase in electricity consumption rates by 7.6% from 1980 until 1998 (Hirschhausen and Andres, 2000). The Chinese government has a target growth rate of 7% per year for this decade (Shiu and Lam, 2002).

To illustrate the similarity between the countries performance annual changes in per capita GDP and electricity demand were plotted in Figure 4.6 for Japan, South Korea and Thailand. The three economies are shown to be similar in their response to economic shocks in 1980 and in 1997. Figure 4.7 shows this for the same three countries. The broad patterns are fairly similar across the three economies although the magnitude of the ratio differs. It is interesting to note that the ratio for Thailand is very similar to South Korea.

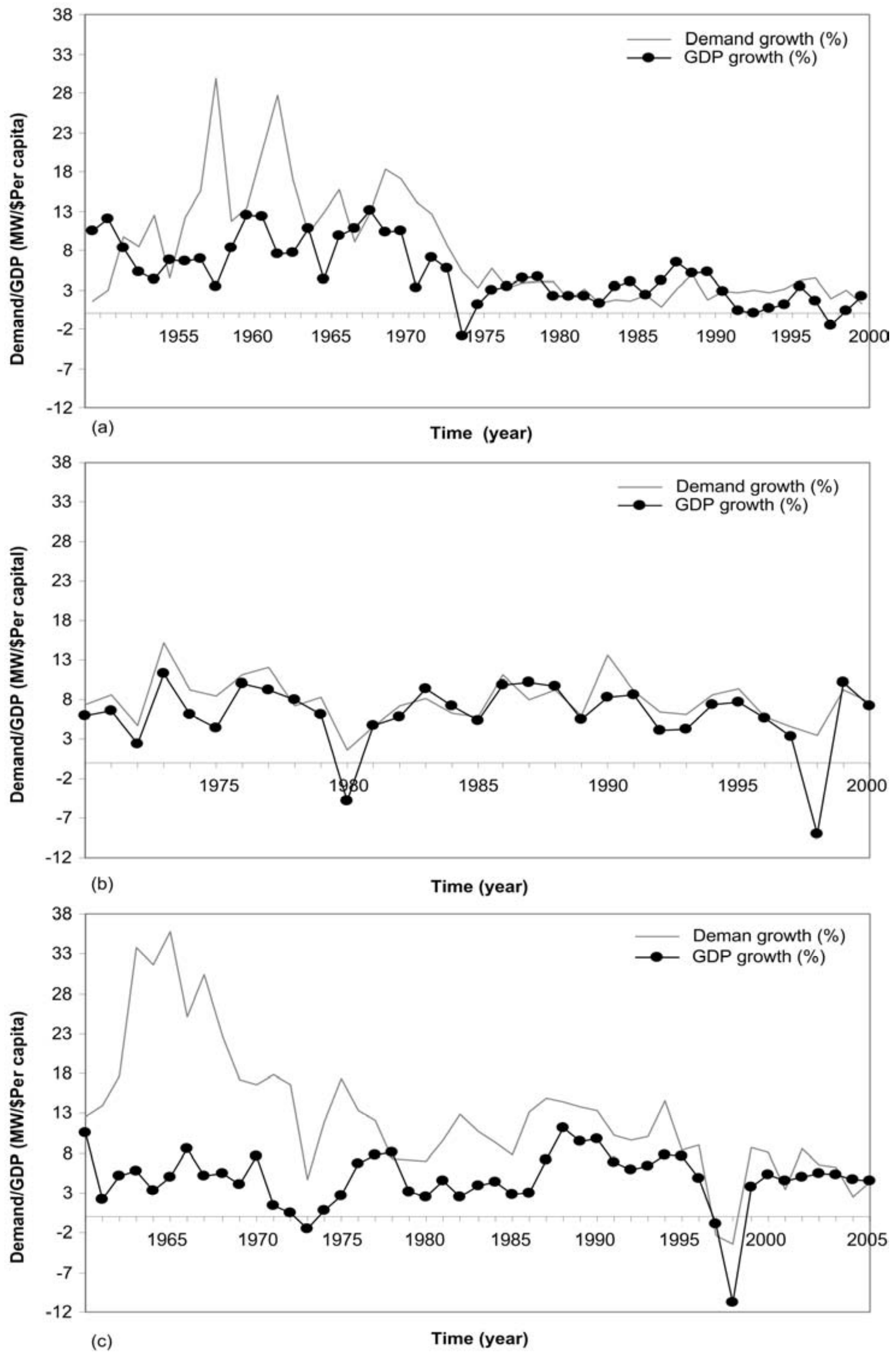

Figure 4.6: Comparison of growth rates in electricity demand and real per capita GDP in (a) Japan, (b) South Korea and (c) Thailand.

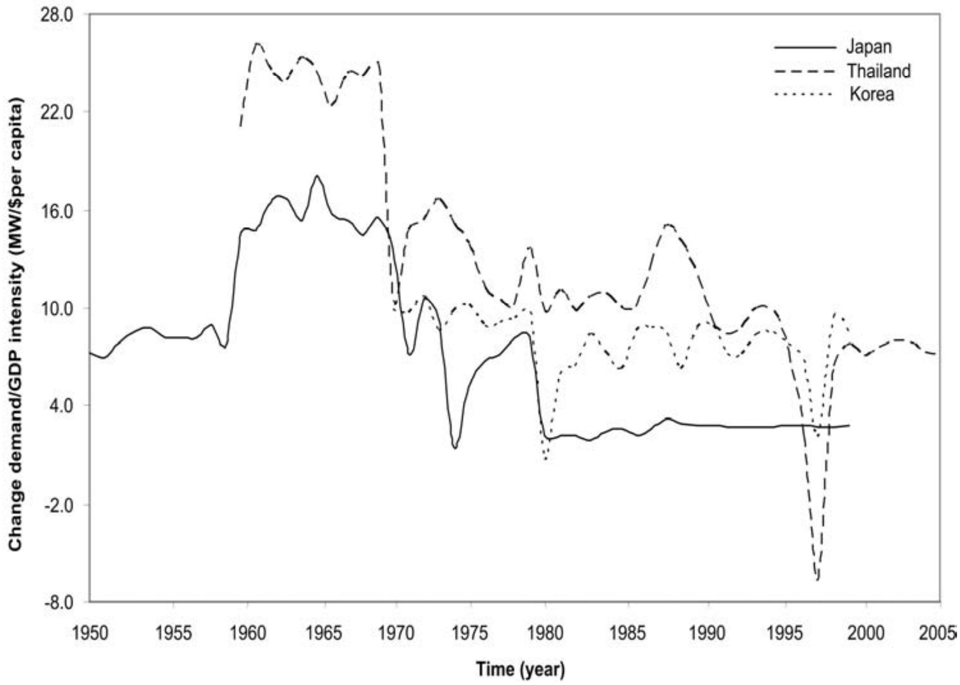

Figure 4.7: Electricity consumption and real GDP per capita intensity between Japan, Korea and Thailand from 1950 to 2005.

4.2.2 Future demand forecasts

The link between GDP and electricity demand is commonly used as a means of forecasting future electricity demand. Future levels of economic growth and population growth are not known with certainty and are subject to many complex factors. The economic crisis of 1997 is a good example of an event that was not foreseen by forecasters. With uncertainty surrounding GDP and population forecasts, any forecasts of electricity demand based on them will also be uncertain.

As outlined in Chapter 2 for the SRES emissions scenarios, scenarios are a common way of coping with uncertainty. The bodies that forecast Thailand's electricity demand also use scenarios of desirable or possible economic growth to understand the range of demand levels that may occur. A recent long term forecast by EPPO (2004) uses three scenarios that differ in their estimate of economic growth although population growth is assumed to be the same in each case. The scenarios are target economic growth (TEG), which is a high level of growth, Moderate Economic Growth (MEG) and Low

Economic Growth (LEG), which are progressively lower. Table 4.3 shows the three Thailand Development Research Institute (TDRI) projections of GDP annual growth over the period from 2003 to the end of 2016. All show a slight reduction in growth rates over the period but there is a big range of economic growth rates: simple average annual growth rate of 4.1% for the LEG, 6.5% for the MEG and 7.6% for the TEG in year 2003 to 2016. The compounding effect across the 14 years is large and suggests the Thai economy will grow by between 74 and 182% between 2003 and 2016.

Year	LEG (GDP %)	MEG (GDP %)	TEG (GDP %)
2003	6.0	6.0	6.3
2004	4.0	6.5	8.5
2005	4.0	6.5	10.0
2006	4.0	6.5	8.0
2007	4.0	6.5	7.5
2008	4.0	6.4	7.4
2009	4.0	6.4	7.4
2010	4.0	6.6	7.6
2011	3.9	6.5	7.5
2012	3.9	6.5	7.5
2013	3.8	6.5	7.5
2014	3.7	6.4	7.4
2015	3.8	6.5	7.5
2016	3.7	6.4	7.4

Table 4.3: Thailand's GDP growth forecasts, 2003 to 2016 (EPPO, January 2004).

The consequent increases in electricity demand are forecast to be very large as Figure 4.8 shows for peak demand (left) and energy consumption (right) forecast for the three scenarios. The simple average annual growth in Thai peak electricity demand growth over the period from 2003 to 2016 is estimated to be 4.9% for the low growth scenario, 7.1% for medium growth and 8.6% for the high, target growth rates. The simple average growth in energy consumption is similar at around 4.8% (LEG), 6.9% (MEG) and 8.3% (TEG) (EGAT, 2004). The compounding effect results in very large increases in demand over the period: peak demand may rise 80 to 190% (14368 to 34599MW) while energy consumption may rise 80 to 187% (94 to 222TWh).

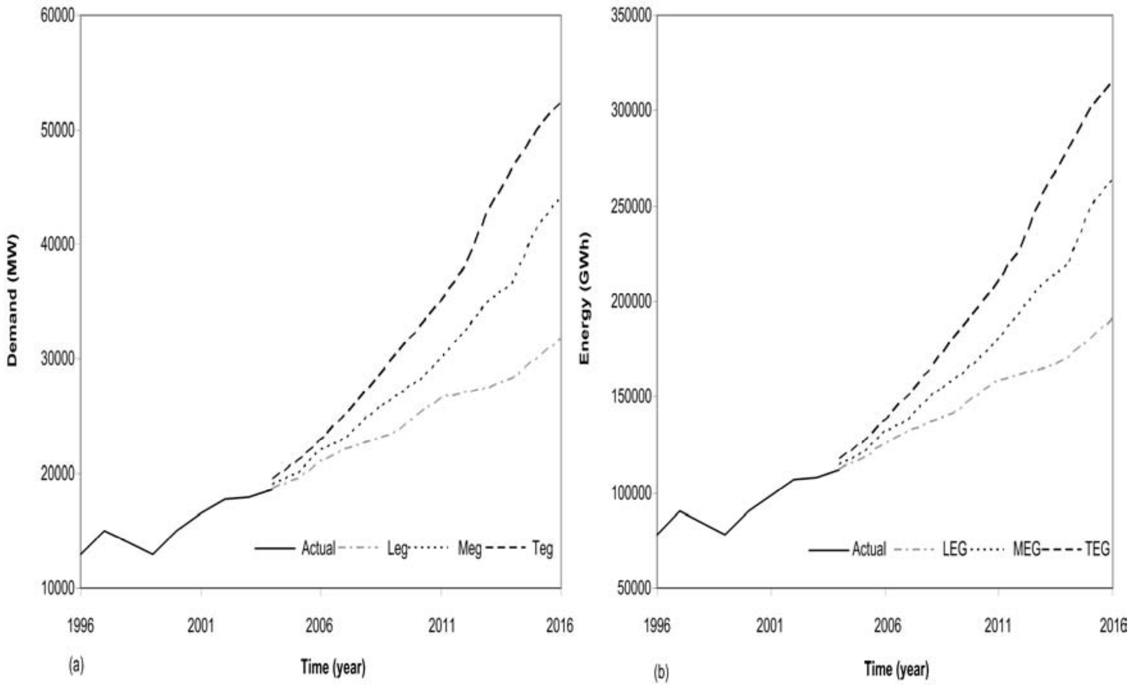

Figure 4.8: Historic and future forecasts demand growth (a) electricity demand and (b) energy demand (EPPO, January 2004).

4.2.3 Demand Sectors

Every user of electricity will consume energy at different times of the day and over the year. Despite significant differences, however, it is possible to create categories of user. Figure 4.9 shows the aggregate measured electricity consumption pattern for 2004 for seven EGAT customer categories. It can be seen that there are major differences between domestic use and industrial use. The business sector consumes 18% of Thailand's electricity, the residential sector uses 25%, industry uses 35% and the remaining sectors (government, specific business and small general service) consumes 22% (Thailand 2004). Overall, electricity is used for lighting (17%), air-conditioning (22%), refrigeration (17%), heating (3%), motor use (31%) and other (10%) (EGAT, 2003).

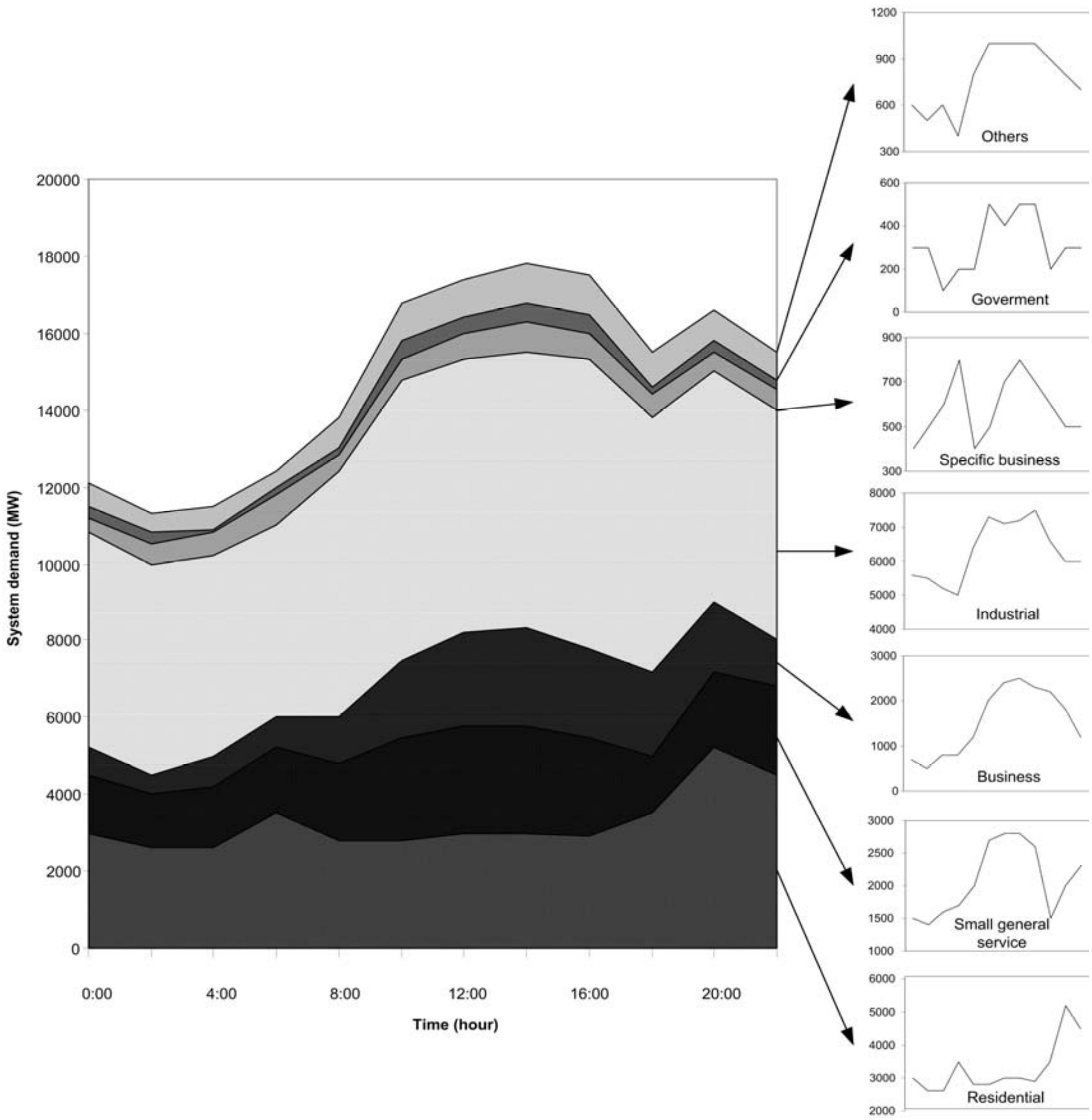

Figure 4.9: Measured hourly electricity consumption pattern for seven customer categories in Thailand by EGAT sector in 2004 (EGAT, 2004).

A breakdown of the 2004 annual electricity consumption in the residential, commercial and industrial sectors is shown in Figure 4.10 Residential electricity consumption is not dominated by any one use. The largest uses are for air-conditioning, refrigeration and lighting. Although heating appears to be a large proportion of domestic demand this is mainly for water heating rather than space heating. As such, a substantial portion of Thai domestic demand consists of weather-sensitive load. Much of the commercial sector is also temperature sensitive as the sector uses over 50% of their electricity for air-conditioning as the working day coincides with the hottest temperatures. The Industrial sector is much less sensitive as 82% of its electricity is consumed by motors

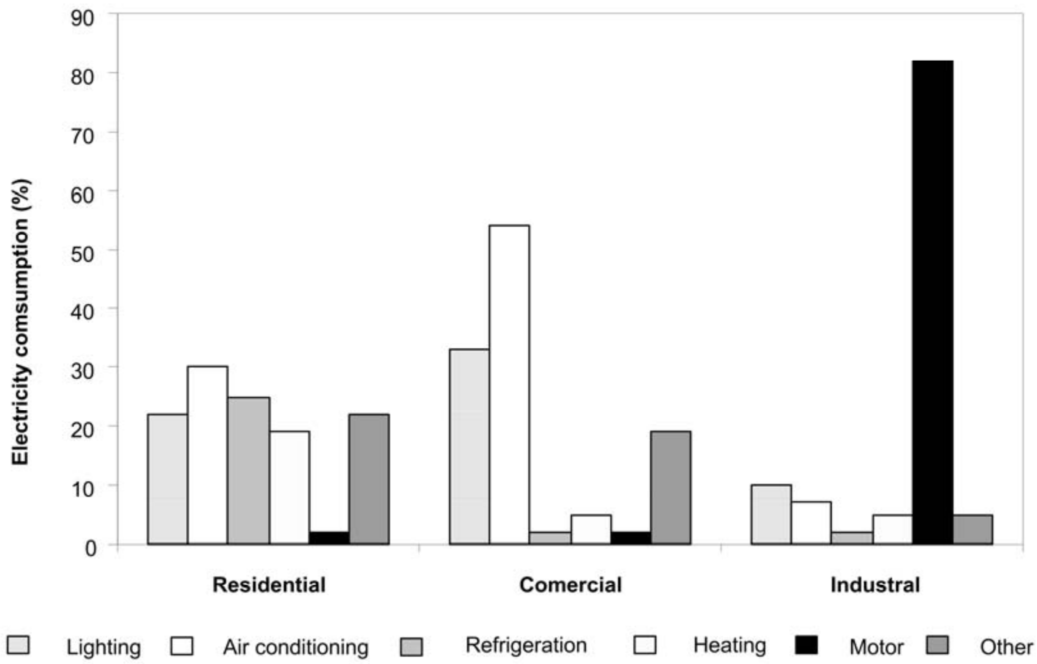

Figure 4.10: Percentage uses of electricity in Thailand for 2004 by sector.

Typical daily load profiles for the three main types of electricity consumers can be seen in Figure 4.11. Both commercial and industrial loads tend to be largest during office hours with the industrial load showing a more constant load in this period reflecting the use of machinery. The commercial profile tends to have a smoother profile reflecting the build up of heat within commercial buildings during the day. Domestic load shows a small peak during the morning as people get out of bed and prepare for work but the substantial loading and the overall peak occurs in the evening once people return from work, turn on lights, cook and use air-conditioning.

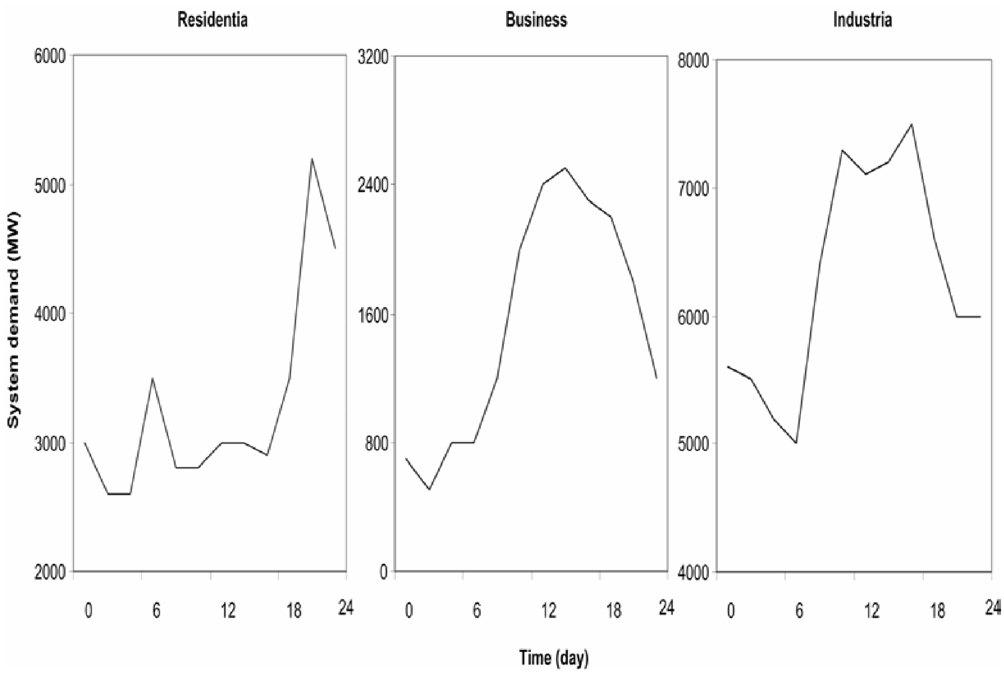

Figure 4.11: Three customer sectors and their electricity consumption over a typical Thai day in 2004.

The characteristics of the demand sectors can be characterised by the relationships between peak and average demand, specifically the load factor which gives the ratio of average demand to maximum demand:

$$\text{Load Factor (\%)} = 100 \times \frac{\text{Average Demand (MW)}}{\text{Maximum Demand (MW)}} \tag{4.1}$$

Domestic load has a relatively low load factor of 63% which means that peak demand is relatively much larger than average. Commercial load factor is lower still while industrial load has a high load factor of 83% which indicates the more constant consumption pattern. Table 4.4 summarises the key characteristics of the three large customer types.

Parameter	Unit	Residential	Business	Industrial
Average demand	MW	3283	1533	6283
Maximum demand	MW	5200	2500	7500
Time of maximum demand	h	20:00	14:00	14:00
Load Factor	-	63%	61%	83%
Energy Usage	GWh	3.9	1.8	7.5

Table 4.4: Load characteristics for three customer types.

4.2.4 Seasonality

Thailand's electricity demand is influenced by the seasons which are commonly classed as summer (March to May), monsoon (normally June to August) and winter (November to January). Figure 4.12a shows the mean daily profile for aggregate demand in 2004 in the winter, summer and monsoon seasons. Summer electricity demand exceeds that of the winter and monsoon but the daily patterns are similar. Demand starts to increase around 8am, achieving a peak around 2pm before falling back, then picking up again in the evening. The lighting load in the evening is a constant feature across all seasons given the limited variability in sunset times across the year. With a hot, humid climate, these variations within the day and across seasons are related to temperature with the hotter temperatures in summer increasing demand for air-conditioning. In contrast, the lower temperatures in the winter and monsoon seasons result in a decrease in demand. The relationship between demand and temperature is shown in Figure 4.12b which is a scatter plot of mean daily demand with Cooling Degree Hours (CDH) in different seasons in 2004. A base temperature of 24°C was used for calculation of CDH which means that the mean daily temperatures towards the left of the plot are just above 24°C. There are three distinct clusters: in black, the lower cluster represents the winter demand; in grey, the higher cluster shows the summer and the white circles towards the middle of the range show the monsoon demand. Their positions reflect the differences in temperatures in each season. The summer season has a relatively high correlation coefficient of determination (R^2=0.75) with lower values for winter (R^2 = 0.42) and the monsoon (R^2 = 0.50). The very specific clusters and the different relationships between seasons (e.g. different gradient between demand and CDH) show that it is necessary to account for seasonality in modelling Thailand's demand.

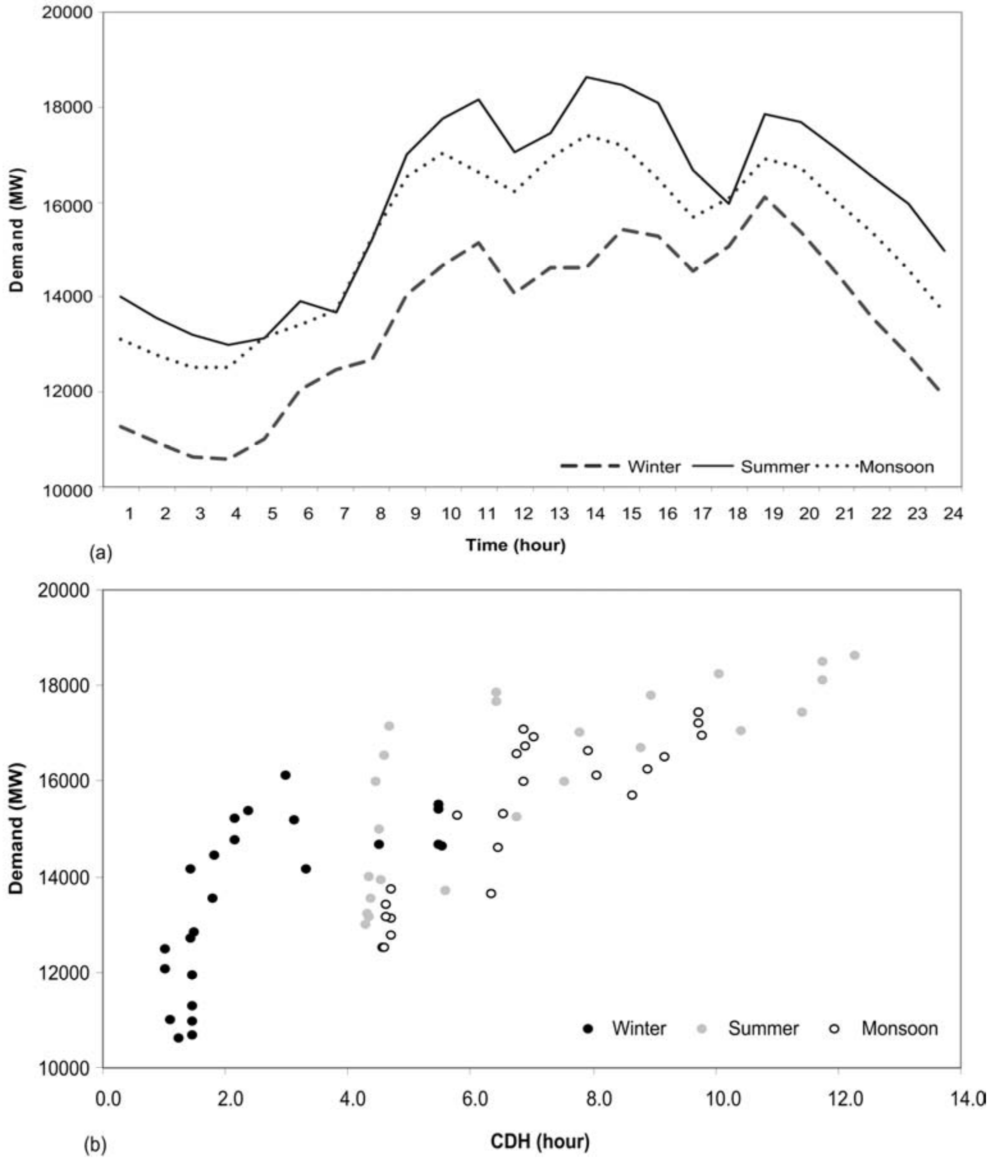

Figure 4.12: Mean daily electricity consumption profiles (a) mean daily demand profile and (b) scatter plot for winter, summer and monsoon over year 2004.

A feature of Thailand's climate is the Monsoon which involves very heavy rainfall at specific times of the year. Rainfall has a significant impact on demand as Figure 4.13

shows. The demand for three consecutive days in June 2004 is plotted: the first on which it rains and the final two on which it is sunny. It can be seen that for both clear days on Thursday and Friday, the profiles are similar and the peaks coincide. The large drop in electricity consumption on the rainy day on Wednesday was due to corresponding fall in temperature during working hours which occurs as the rain takes the heat from the air.

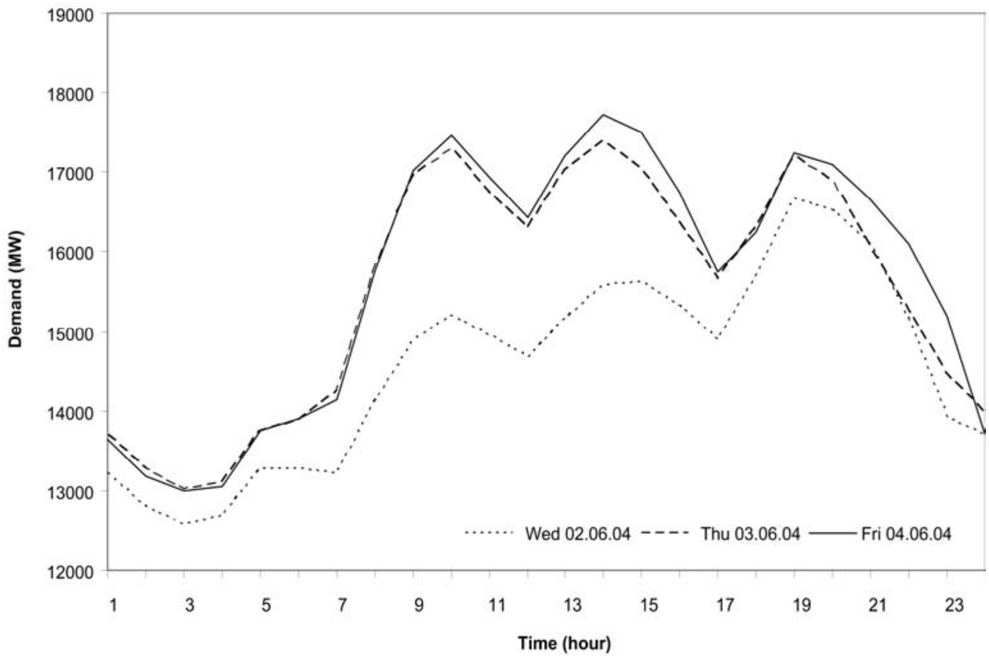

Figure 4.13: A comparison of electricity consumption between clear day and rainy day in June 2004.

4.2.5 Daily Consumption Patterns

Domestic, commercial and industrial demand in Thailand varies considerably across the week as a direct or indirect result of daily work patterns. Figure 4.14 shows daily electricity consumption over weekdays and the weekends for each season. There is significant demand variation within each day but the consumption patterns for weekdays tend to be similar. Weekend consumption tends to be lower than week days as there is less commercial and industrial activity on Saturdays and virtually none on Sundays. The lower weekday demand in winter means that the difference with weekends is less marked than in other seasons.

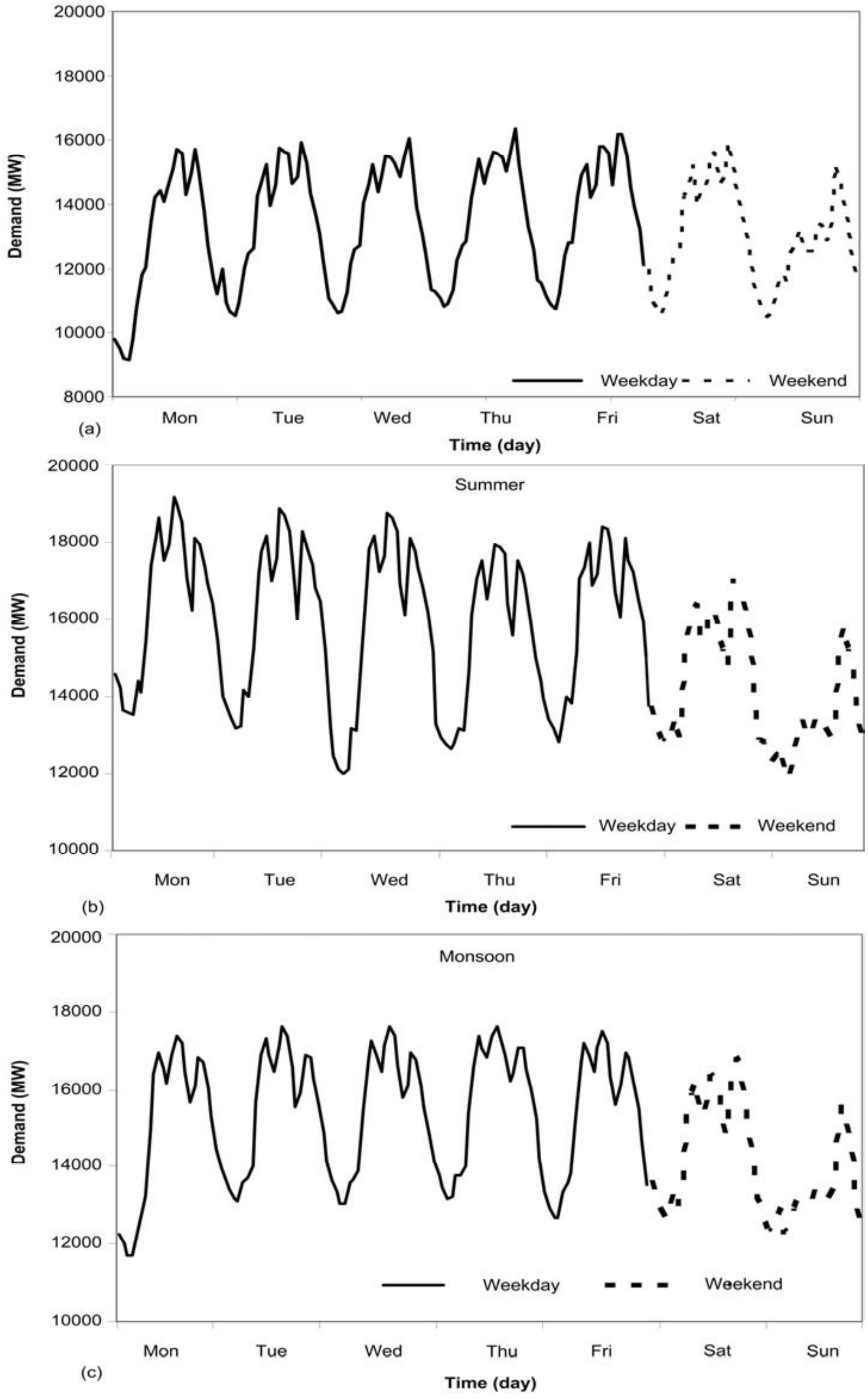

Figure 4.14: Electricity consumption patterns of a typical week during (a) winter, (b) summer, and (c) monsoon in 2004.

There are major differences in demand between public holidays, such as Thai New Year and a normal week. Figure 4.15 illustrates the demand curves of a two week period from the 5th to the 18th of April 2004. The left half of the plot shows a normal week with weekday load mutually similar and lower on Saturday and Sunday. The second half of the plot shows the week-long Thai New Year public holiday. The demand is very different as the weekdays are no longer similar and very much lower than normal. The pattern shows a progressive shutdown of commercial and industrial activity in the early part of the week, several very low-demand days and a steady return to more normal demand levels. The weekends either side of the holiday are fairly typical of others during April.

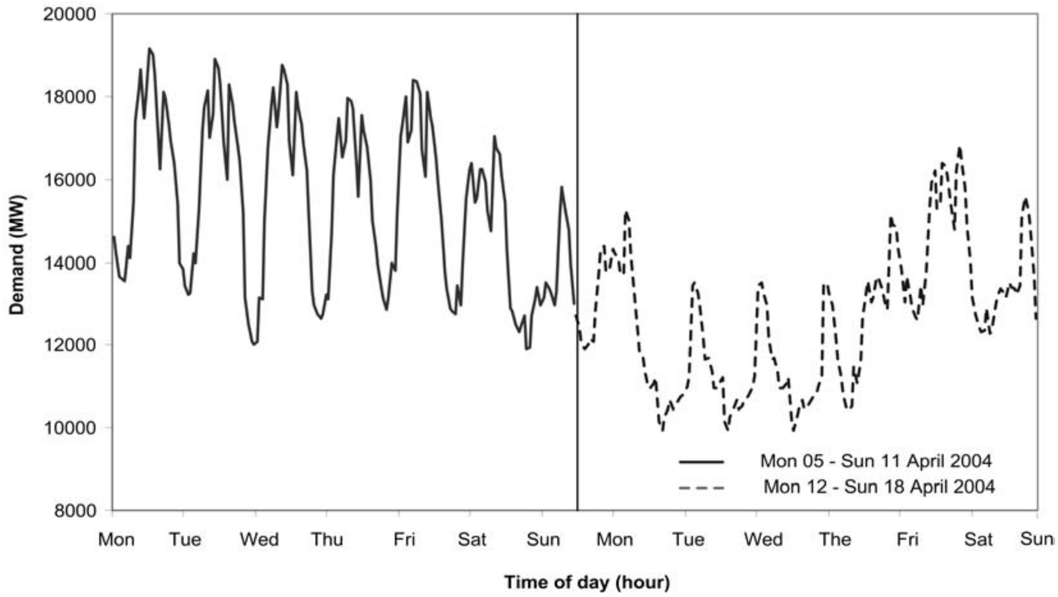

Figure 4.15: A comparison of electricity consumption for a typical week and a holiday week in April 2004.

4.3 Chapter Summary

This chapter describes the characteristics of the Thai electricity industry and in particular its electricity demand. The rapid growth in demand has been presented along with the differences between different demand sectors, the influence of the seasons, type of day and the significant role that weather plays in electricity consumption.

Chapter 5

Modelling the Impact of Climate Change on Electricity Demand

The aim of this chapter is to define and develop an efficient and effective method for analysing the potential impact of climate change on Thailand's electricity demand. The first section reviews and compares available modelling approaches. Based on the availability of data and the nature of Thai electricity demand, an approach is then justified. Based on this a regression method is specified that uses historic weather data to model daily demand profiles. The effectiveness and accuracy of the method in recreating daily demand profiles across the year is examined. Finally, a basic assessment of hourly sensitivity to uniform changes in weather is demonstrated.

5.1 Approaches to Modelling Electricity Demand

Forecasting is the process of estimating unknown values and typically involves time series analysis. It is used in many businesses and typical applications include (Hamilton, 1983; Clements et al., 2004):

- inventory control and production planning (e.g., product demand),
- forecasting financial information (e.g., interest and exchange rates),
- forecasting economic information such as economic growth, and
- forecasting energy demand.

Demand forecasting is vital in power generation and transmission planning. Forecasts are performed over the short, medium and long-term with each time frame used for different purposes and influenced by different factors. Short-term demand forecasts are typically for one day to one week ahead and are influenced by the weather, the day of the week and television schedules. Short-term forecasts are used for security assessment, economic dispatch and real-time control and security evaluation. Medium-term forecasts are typically for a few weeks up to a few years and are used to assess power generation to match energy demand and plan the scheduling of maintenance. It is influenced by many factors, including seasonality and socio-economic change. Long-term forecasts covers the timescale of 5 to 25 years ahead (Saleh, 1996). They predict the peak and average yearly demand to allow planning of generation and transmission expansion plans or to guide long-term investment by suppliers to target demand growth. Long-term forecasting is complicated as demand is strongly affected socio-economic by factors such as increasing population and economic growth.

Forecasting is an established technique and is used by utilities to forecast demand and energy use. A wide range of methods are used including econometrics, time series and artificial intelligence.

5.1.1 Regression Methods

Regression models express the relationship between independent variables and a dependent variable. For an application such demand modelling the independent variables could be weather, time of day and previous demand, with demand as the dependent variable. Regression methods are classified into two groups, parametric and non-parametric.

Parametric regression methods are frequently used to describe the association between load and factors affecting load. The model parameter of the regression requires the regression equation to be chosen based on one or more known parameters. Parametric regressions typically use a small number of parameters which often have some physical meaning (Makridakis et al., 1998). Parametric models include Multiple Linear Regression (MLR) and polynomial regressions. Non-parametric regression differs as there is little or no prior knowledge about the form of the true function which is being estimated. The function is still modelled using an equation but in a way which allows the class of functions which the model can represent to be very broad. Typically this involves using many parameters which have no physical meaning in relation to the problem. Kernel smoothing is the most popular non-parametric method for short-term forecasting (Pindyck and Rubinfeld, 1997; Makridakis et al., 1998).

The most simple regression model is simple linear regression or 'least squares regression'. It is used to evaluate the linear relationship between two variables. The example below shows the relationship between temperature and the demand:

$$D_t = \beta_1 + \beta_2(T_t) + \varepsilon_t \tag{5.1}$$

where D_t is electrical demand in hour t, T_t is the temperature, β_1 and β_2 are parameters that must be estimated. The symbol ε_t represents the random error term which typically has zero mean and constant variance (i.e., white noise).

Multiple Linear Regression (MLR) is commonly used for forecasting because of its flexibility and ease of application. It can be used as a stand-alone method for load forecasting, or to define a function in a time-series load forecasting model. In MLR the forecasted load is expressed in terms of variables such as weather and other factors which influence the electricity demand. The MLR model is given as:

$$D_t = \beta_1+\beta_2(X_2)+\beta_3(X_3)+\ldots\ldots+\beta_n(X_n) + \varepsilon_t \tag{5.2}$$

where $X_2,\ldots,.X_n$ are variables related to demand and $\beta_1, \ldots, \beta_n$ their regression coefficients. A schematic of an MLR is given in Figure 5.1 which includes variables that represent specific hours; these would normally be included as dummy variables.

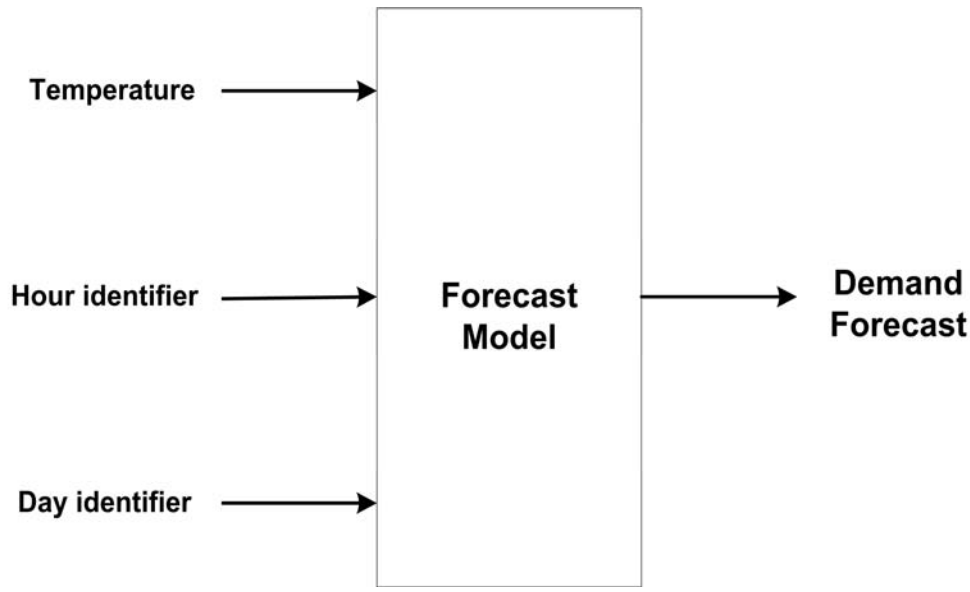

Figure 5.1: Schematic diagram of a MLR forecast model (Adjepon-Yamoah, 2001).

5.1.2 Time Series Methods

Time series methods use the time-dependent relationships between variables to predict future values. They are commonly employed in short-term and long term forecasting in the power generation industry. Time series methods have several advantages and disadvantages over regression models. The principal advantage is their simplicity but they do not directly describe a 'cause and effect' relationship, only one of time dependency. On their own, such models cannot provide insight into the demand/weather relationship.

Many time series methods rely on 'autocorrelation' which is a measure of how well a signal matches a time-shifted version of itself (Makridakis et al., 1998). Autocorrelation is useful for finding repeating (or periodic) patterns in a time series which otherwise are hidden by noise. The autocorrelation function shows how well a time series is correlated with itself as a function of the amount of time shift.

Autoregressive (AR) Processes

Autoregressive (AR) models express the future value of the time series as a linear regression of the current value of the series with one or more previous values of the time series. The order of the model depends on the oldest previous value used in the regression. This allows extrapolation from historical data sets where the correlation is positive or negative. It takes the form (Makridakis et al., 1998):

$$D_t = \beta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_n X_{t-n} + \varepsilon_t \tag{5.3}$$

where: β is a constant term, X_{t-n} are previous demand values, and ϕ_n are autoregressive model parameters (correlations).

Moving Average (MA) Processes

In a Moving Average (MA) process the current value of the demand D_t is based on relationships with the error terms in the time series. The name moving average does not arise from the averaging of the time series itself and as a result MA models have a less obvious interpretation than AR models (Makridakis et al., 1998). The MA is defined as:

$$D_t = \beta + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_1 \varepsilon_{t-n} \tag{5.4}$$

where: θ_n are the moving average coefficients.

Autoregressive Moving Average (ARMA) Process

The basic features of the AR and MA models can be combined to produce a range of more complex models. The Autoregressive Moving Average (ARMA) model incorporates both the auto-regression (AR) and the moving average (MA) model. It captures both the self-correcting nature of the moving average method whilst expressing the demand as a function of previous demand. It takes the form,

$$D_t = \beta + \phi_1 X_{t-1} + \ldots + \phi_n X_{t-n} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_1 \varepsilon_{t-n} \tag{5.5}$$

Autoregressive Integrated Moving Average (ARIMA) Process

AR, MA and ARMA models assume that the time series is stationary. That is where the statistical patterns, specifically the mean and variance, do not change over time. To handle non-stationary time series, the more general Autoregressive Integrated Moving Average (ARIMA) model is used. The ARIMA method was developed by Box and Jenkins (1976). This introduces a process called differencing which relates values that lag each other by a specified amount such as one or more periods and serves to reduce more complex patterns like seasonality into a simpler stationary form. The differencing adds significant complexity to the algebra so it is common to use the backshift operator B to capture the time shifting. The operator appears to shift the data back one time step with BX_t being equivalent to X_{t-1} and $B^{12}X_t$ equal to X_{t-12}. The simplest case using a first order AR and MA process and a single time shift can be written neatly as (Makridakis et al., 1998):

$$(1 - \theta_1 B)\ (1 - B)\ X_t = \beta + (1 - \theta_1 B)\ \varepsilon_t \tag{5.6}$$

The complexity is illustrated in Figure 5.2 which shows the process for fitting an ARIMA process (Ouenniche, 2005) An AR regression model is fitted to generate the model error. The errors are then checked for stationarity: if they are non-stationary the differencing process is used to remove patterns like seasonality and the AR model re-fitted using the new series. Once the errors are stationary an ARMA model is identified and the entire model is re-fitted and the errors checked to look random. Although complex, the short-term and long-term forecasting results for ARIMA are good (Chao-Ming Huang, 1995).

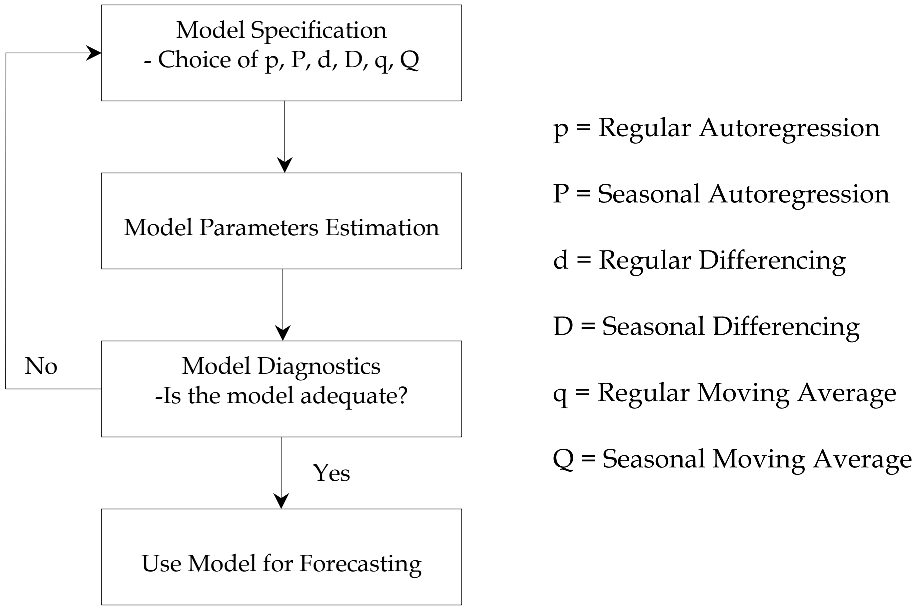

Figure 5.2: ARIMA forecasting model procedure (Ouenniche, 2005).

5.1.3 Artificial Intelligence

Artificial intelligence forecasting techniques such as expert systems (Rahman and Bhatnagar, 1988). and particularly the Artificial Neural Network (ANN) (Lu et al., 1993; Papalexopoulos et al., 1994) have been used for forecasting electrical loads.

An ANN models the activity of neurons in the brain and the connections between them. Each neuron is a simple processing unit which receives and combines signals from many other neurons. If the combined signal is strong enough it activates the firing of the neuron, which produces an output signal. A typical neuron is shown in Figure 5.3. The input of the neuron is the weighted sum of all outputs from the neurons in the previous layer. Should the value of the weighted average be greater than a given threshold then the output *Aj* takes a defined value. The neuron serves as a nonlinear transfer function to transform its input to be the output, which contributes to the input for neurons in the next layer.

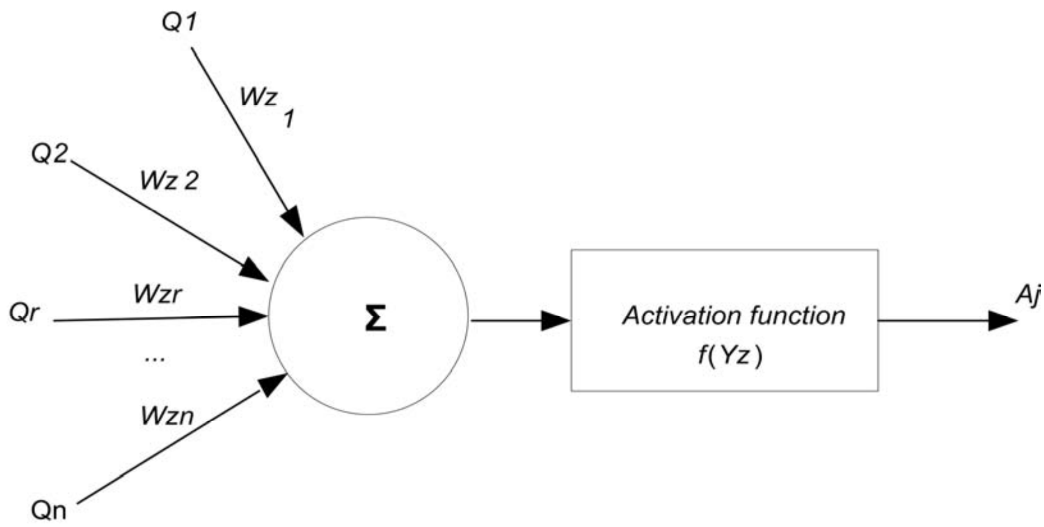

Figure 5.3: Schematic model of an ANN neuron (Sailor et al., 1999).

A neural network consists of many neurons joined up in the manner described. The neurons are organised into groups known as layers. The number of layers and their interconnection depends on the problem but there is always an input layer, where data is presented to the network and an output layer, which holds the response of the network. The layers in between the input and output are called hidden layers and provide the modelling power of the neural network. The input layer, hidden layer and output layer from the network can be vectors of any size (Schalkoff, 1997). Neurons in one layer only connect to neurons in the neighbouring layers. The ANN is referred to as fully connected when the output each neuron is connected to the input of every neuron in the next layer. Since each connection has a corresponding weight, the signals on the input lines will be modified by these weights prior to being summed up. A three layer fully connected feed-forward neural network is shown in Figure 5.4.

ANNs are widely applied in short-term forecasting (Madan and Bollinger, 1997) where weather indicators form a key input. ANNs are attractive because of their ability to model an unspecified non-linear relationship and can be viewed as a non-parametric regression.

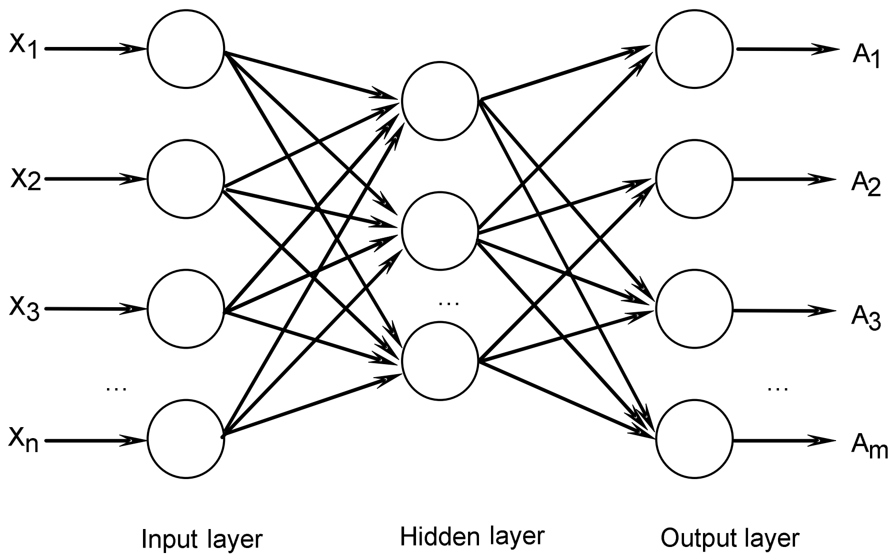

Figure 5.4: Schematic of a three layer artificial neural network (Sailor et al., 1999).

5.1.4 Comparison of methods

Various forecast models have been presented and each method has advantages and disadvantages in being able to be applied to the problem of modelling climate change impacts on electricity demand in Thailand.

Time series models use historical data to obtain future hourly, daily and seasonal loads. The disadvantage of these models is that they model a stationary load trend. Even after incorporating transfer functions, the weather and any other dynamic factors that contribute to demand are not fully utilised within the forecast. If applied on their own a time series method could lead to poor ability to reproduce weather effects.

Regression methods analyse the relationship between the demand and influential variables. Linear regressions represent relationships linearly so polynomial or logarithmic regressions can be of benefit for non-linear cases. Non-parametric regression provides potentially appropriate fits but requires very complex modelling techniques and a heavy computational effort. While parametric regression models have the advantage of simplicity they may not capture the full range of dynamic factors within the time series.

A potentially powerful approach is to create a hybrid demand model incorporating both time series and regression methods. This would allow the time series methods to account for seasonality, and other periodic elements, while the regression captures the relationships between demand and climate variables.

Artificial neural network based systems model the knowledge of a human expert to develop the rules for forecasting. Transforming the knowledge of an expert to a set of mathematical rules is often very difficult (McCulloch and Pitts, 1943). ANNs can produce very good forecasts but there are difficulties when forecasting beyond the boundaries of the training data set. This is because forecasts are based on a discrete set of historical conditions. ANN methods are able to learn and extract complex relationships from multivariate data. Their main disadvantage is that they provide a black box solution and it is very difficult to assess the effect of individual variables (Daneshdoost et al., 1998).

5.2 Definition of Modelling Approach

5.2.1 Modelling considerations

The requirement was for a model or models that allowed anticipated changes in temperature (and potentially other climate variables) to be used to indicate future changes in daily and seasonal load profiles with a particular interest in peak demand levels. The choice of approach was a complex process, involving not only the type of models (regression, ANN, etc.) but also a range of other factors needing consideration. The issue of data availability was of critical importance but the following issues were significant:

- which demand-related effects to consider,
- the degree of aggregation,
- the level of spatial and temporal detail required, and

- the climate variables of interest.

The mean temperature of Thailand is around 31°C (based on data from 1996 to 2004) within a typical annual range of 22°C to 39°C. As highlighted in Chapter 4, there are very limited space heating requirements in Thailand particularly not in the Bangkok metropolitan area. This simplifies modelling by limiting the assessment to consideration of the dominant cooling effects only.

The degree of aggregation affects the potential accuracy and level of detail possible. There are two opposite approaches: bottom-up models and top-down models. Bottom-up demand models for key sectors (e.g., domestic, commercial, industrial) would potentially allow accurate weather-dependent demand projections to be made. The downside to this is the very large range of data required which includes detailed demographic and economic information, load characteristics like building construction, air-conditioning take-up, as well as availability of meteorological and electricity demand data. This information is perhaps more readily available in an industrialized economy rather than a developing nation like Thailand. As a result, top-down models were investigated in more detail (see Section 5.1). These include neural networks (Li and Sailor 1995) and regression models (Hor et al., 2005; Linder et al., 1987). While neural networks can capture complex relationships they require significant data volumes for training purposes. In addition, the hidden nature of the relationships did not fit with the author's desire to be able to 'see' the detail in order to interpret it. The use of a top-down method is not believed to be a major shortcoming as Linder et al. (1987) found comparable results from regression-based and more complex sectoral planning models. A key point is that using projections with such models there is an implicit assumption that the relationships hold over time. However, the benefits of a simpler model appear to offset this risk as well as being more feasible with regards to data availability.

The spatial detail required or possible is based on how uniform the power system is in terms of demand, urban and rural balance as well as the availability of climate and demand data. The electricity demand data made available by EGAT consisted of hourly aggregate demand for the whole of Thailand over the period 1996-2004. In addition, hourly weather information for the same period was available from a weather station in the Bangkok metropolitan area; other weather stations only held daily maximum and minimum data. As over 70% of Thailand's electricity is consumed in the Bangkok metropolitan area and with limited meteorological coverage elsewhere, the aggregate system demand was considered to be reasonably representative of the system as a whole.

The aim in the assessment was to provide as much temporal detail as possible to capture the effect of not just mean temperature changes but also changes in the diurnal temperature range (difference between maximum and minimum daily temperature). This would allow changes in daily load profiles and particularly the relative size of peak and off-peak demand response to temperature changes to be seen. Analysis of degree days (e.g. Venäläinen et al., 2004; Hulme, 2002) could not provide this level of detail but a variation on this using hourly weather and demand data would allow detailed sub-daily analysis.

As mentioned in chapters 3 and 4, electricity demand is affected by atmospheric conditions such as temperature, rain, cloud cover, humidity and wind speed. The choice of which climate variables to apply depends on their relative influence. Hamadi Al and Soliman (2004), Hor et al. (2005) and others identify temperature as the major factor with other variables having a secondary effect (Li and Sailor, 1995) ; (Valor et al., 2001).

5.2.2 Modelling Approach

The desire to be able to project changes in demand on a time-of-day, day-of-week, and month-of-year basis for times many years in the future was a challenging task. Modelling these changes in a single unified model would have involved modelling hourly demand response to temperature together with factors describing demand change over the longer term (e.g., GDP and population). Although an ANN would have lent itself well to such a task, such a model would have been very large, required lots of data for training and difficult to develop, calibrate and interpret. It would also have been feasible to create a hybrid time series – regression model although this would also have been quite complex. Given the limited data available for Thailand, a simpler, two-part approach was adopted which was similar to that of Linder et al. (1987):

1. The first part of the model describes hourly demand in each month based on weather information. It is used to project changes in demand with changes in climate variables. It is described below.
2. The second part of the model allows these changes to be translated into the future using long-term models. A description of it and its integration with the first part of the model is given in Chapter 6.

Weather Sensitivity Model

Of the modelling considerations set out earlier, the main limitation on the analysis is the availability of data. A regression-based approach was identified as being a good compromise. Existing climate impact studies, particularly that by Linder et al. (1987) offered some guidance. One difficulty with the approach is the effect of demand growth which any regressions based on multiple years will implicitly include. Linder et al. (1987) dealt with this by basing their regression on variance from the mean monthly demand, effectively normalising demand. Here, to limit the effect of demand growth a single year – 2004 – was used in the regression. The regression exercise was repeated for several earlier years and the coefficients compared with 2004. It was found that there was good agreement and the comparison is presented in Appendix A for reference.

With the amount of weather-sensitive and other, non-weather sensitive (e.g. TV use) electricity demand varying across the day, a simple multiple linear regression model similar to that in Equation 5.1 would not be adequate. This is because a single dummy variable representing the hour of the day cannot capture the complex underlying patterns in demand and it would be unlikely to be able to capture the influence of differing amounts of weather-sensitive demand present at different times of the day. Instead it was decide to create a series of regression models for specific periods in the day across each month which would characterise the underlying demand and the degree of weather sensitivity. Examples of these 'time-slices' are shown in Figure 5.5 for the hours between 7 and 8am, 1 and 2pm, and 7 and 8pm.

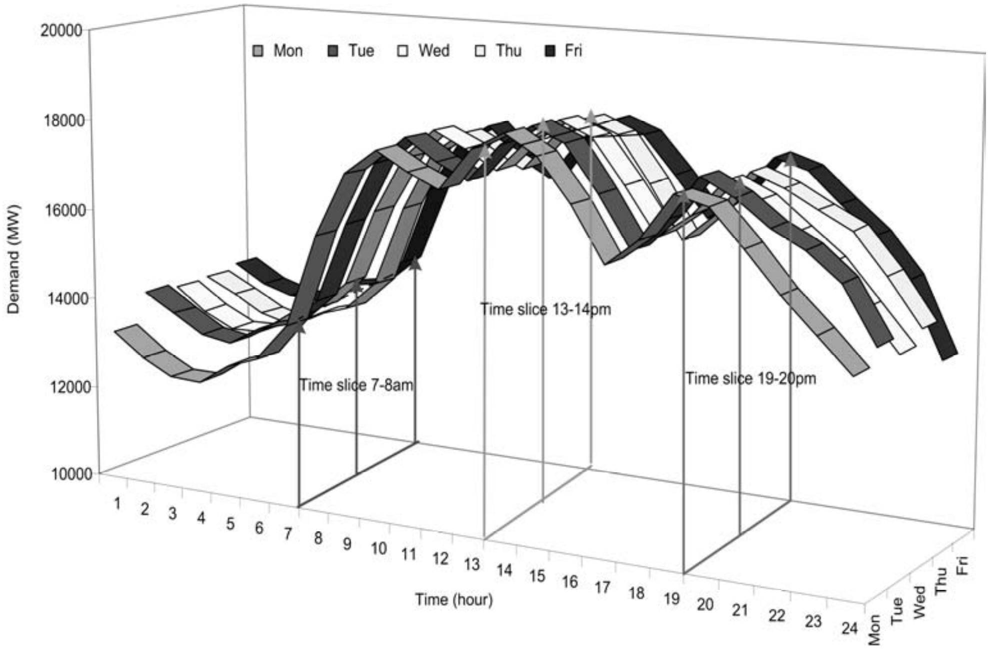

Figure 5.5: Example of 'time-slice' approach.

A wide range of combinations of time steps and weather variables were tested. The most consistent and high quality regressions were for hourly time steps between hourly demand and the temperature-derived Cooling Degree Hours (CDH). The use of atmospheric temperature alone gave relatively poor regression results and relative humidity and wind speed were found to add little to the quality of the relationships. An illustration of the quality of the fit between CDH and demand is given in Figure 5.6 in which there is very good correspondence in average daily patterns in most months except June when the monsoon occurs (the coefficient of determination for 2004 was 0.68). The impact of rainfall has a significant impact on the temperature relationship and it was decided to omit days on which rain fell from the regressions. This issue is briefly examined in the next sub-section but it is not believed to be a major error given the primary interest is in peak load conditions and rain tends to reduce load. Including

rain within the analysis is clearly of interest with regard to potential shifts in the timing of the Monsoon but was considered to be beyond the scope of this work.
The regression for each hourly time-slice is of the form:

$$D = \beta_1 + \beta_{\mathrm{CDH}}\,(CDH) + \varepsilon \tag{5.7}$$

where D is the hourly electricity demand, CDH is cooling degree hour, β_1 is the intercept of the regression line on the demand axis and ε the random error. β_{CDH} is the gradient indicating the sensitivity of demand to cooling degree hours (measured in MW/CDH). CDH are given by:

$$CDH(T_h) = \begin{cases} \sum_{h=1}^{N} (T_h - T_b) & \text{for } T \geq T_b \\ 0 & \text{otherwise} \end{cases} \tag{5.8}$$

where N is the number of hours across the month, T_h is the actual air temperature and T_b is the threshold temperature. In Thailand the threshold temperature is commonly taken to be 24°C.

To account for the differences between demand patterns on weekdays, weekends and public holidays (as highlighted in Chapter 4) it was necessary to create separate sets of regressions for each of these for each month. The total number of regressions in the entire model is 864 (24 hours per day x 3 types of day x 12 months)

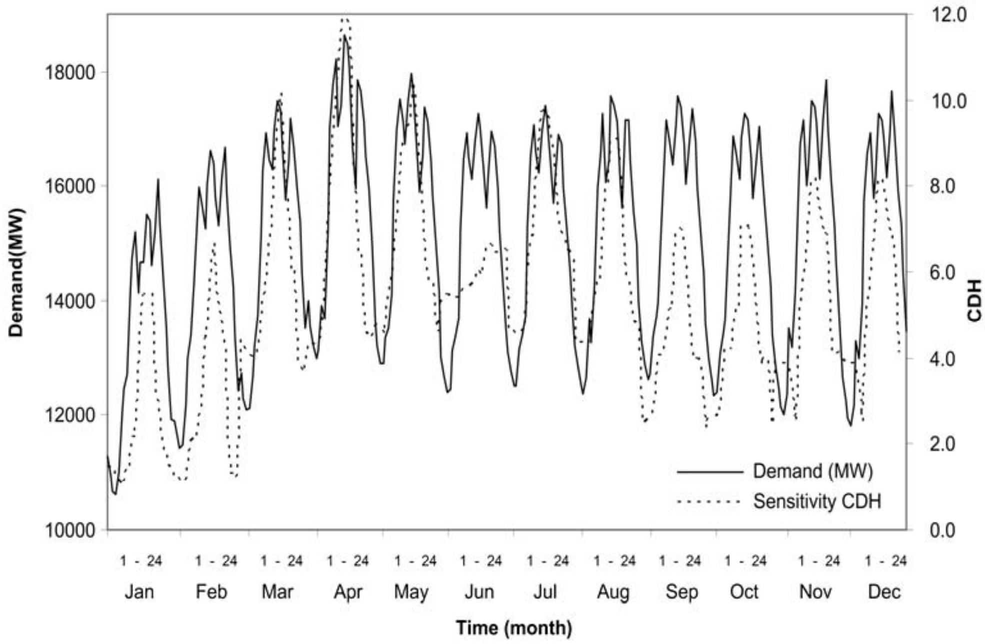

Figure 5.6: Average weekday demand profiles and CDH during the 12 months of 2004.

The model was implemented in a series of Excel spreadsheets which contain the historic demand and weather data as well as the details of each regression. The regressions were created using Excel's 'LINEST' function to calculate the ordinary least squares fit. The accuracy of these was examined with a Matlab script that calculates the coefficients based on matrix inversion. They were found to be in agreement. The regressions provided the coefficients β_1, β_{CDH} and a range of statistical measures of fit including the coefficient of determination.

Assessing the Impact of Rain

The significant difference between the CDH pattern in the Monsoon (June) in Figure 5.6 was investigated further by creating test models of two sets of consecutive weekdays in May 2004. The rainfall data available was not full rainfall data (e.g. mm/day) but was an index of whether rain fell during a specific hour: 1 if rain occurred and 0 if it did not. The second set of weekdays (10 - 14 May 2004) was used to create a set of time-slice regressions of demand and CDH. Figure 5.7a shows the demand profiles of these days and those predicted by the fitted model using Equation 5.7. Over such a short period time the correlation is very good (R^2=0.95) as the error plot for each hour shows (Figure 5.7b) with errors of 0.01 to 3.7%. Figure 5.8 shows the performance when Equation 5.7 was used to fit the model for the week earlier (3 – 7 May 2004) when it had rained on the Wednesday. The results show a poorer fit between modelled and actual demand (R^2=0.50) overall and particularly on the Wednesday itself when errors ranging up to 21.6%. This justified the omission of rainy days from the final regressions.

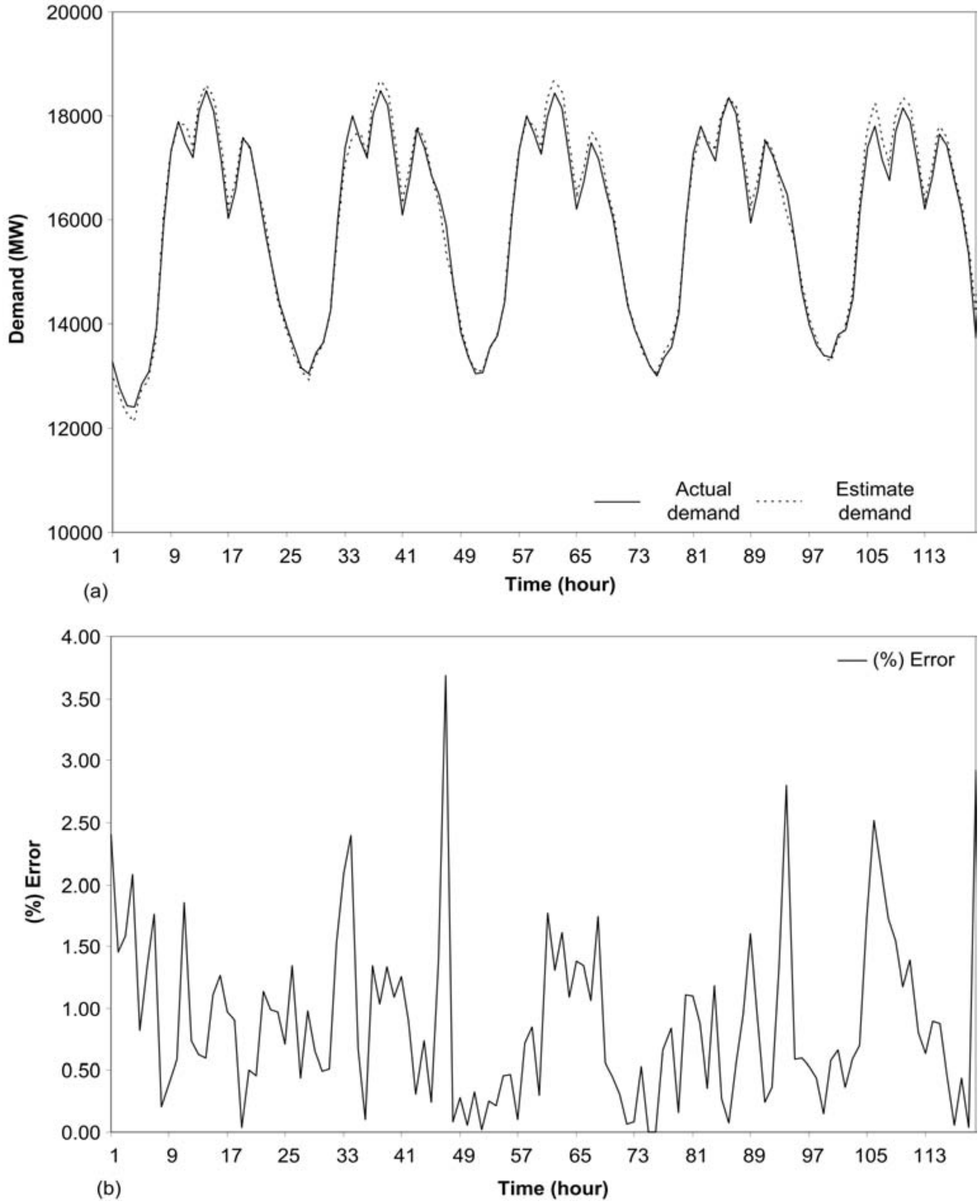

Figure 5.7: Sample clear weekdays from 10-14 May 2004: (a) actual and estimated demand and (b) absolute percentage estimation error.

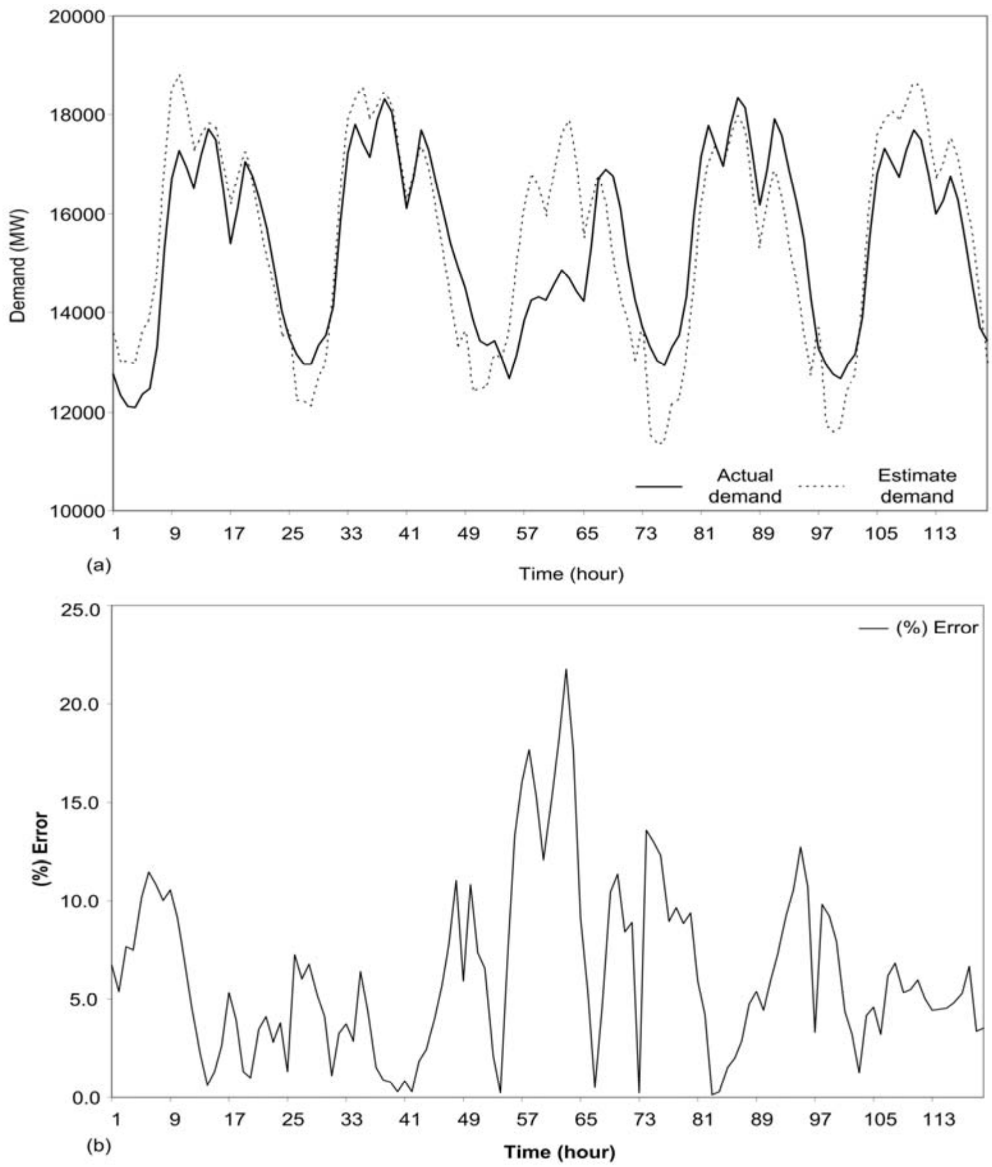

Figure 5.8: Sample weekdays from 3-7 May 2004 where rain fell only on Wednesday (middle of plot) while the other days were dry: (a) actual and estimated demand and (b) estimation error.

5.3 Performance of Weather Sensitivity Models

The regression model for each month for each type was created as indicated in the previous section. Rather than present each and every month in detail here, three key months are presented to indicate model performance. These are January, representing winter, April, representing summer, and July, representing Monsoon. Their results are presented for the three types of day: weekdays, weekends and public holidays.

To evaluate the effectiveness of the model, the estimated demand for each time slice and overall is compared to the actual demand. In addition to the coefficient of determination, the fit can be expressed as the mean absolute error (MAE, MW):

$$\tfrac{1}{n}\sum_{t=s}^{n}\left|L_{forecast}-L_{actual}\right| \tag{5.9}$$

or mean absolute percentage error (MAPE, %):

$$\tfrac{1}{n}\sum_{t=s}^{n}\left|\frac{L_{forecast}-L_{actual}}{L_{actual}}\right|\times 100 \tag{5.10}$$

In both cases n is the total number of hours in the period, $L_{forecast}$ is the modelling demand in hour t and L_{actual} is the actual demand in hour t (Jia et al., 2000; Hamadi Al and Soliman, 2004).

5.3.1 Weekdays

To some extent, the coefficient β_1 indicates the part of electricity demand that is independent of cooling requirements. Figure 5.9 shows the variation in β_1 intercept for weekdays in summer (April), winter (January) and monsoon (July) seasons. The peaks in the β_1 value in the morning and evening reflect the underlying consumption patterns in Thailand. The values for all three seasons are similar although there is some divergence on summer mornings.

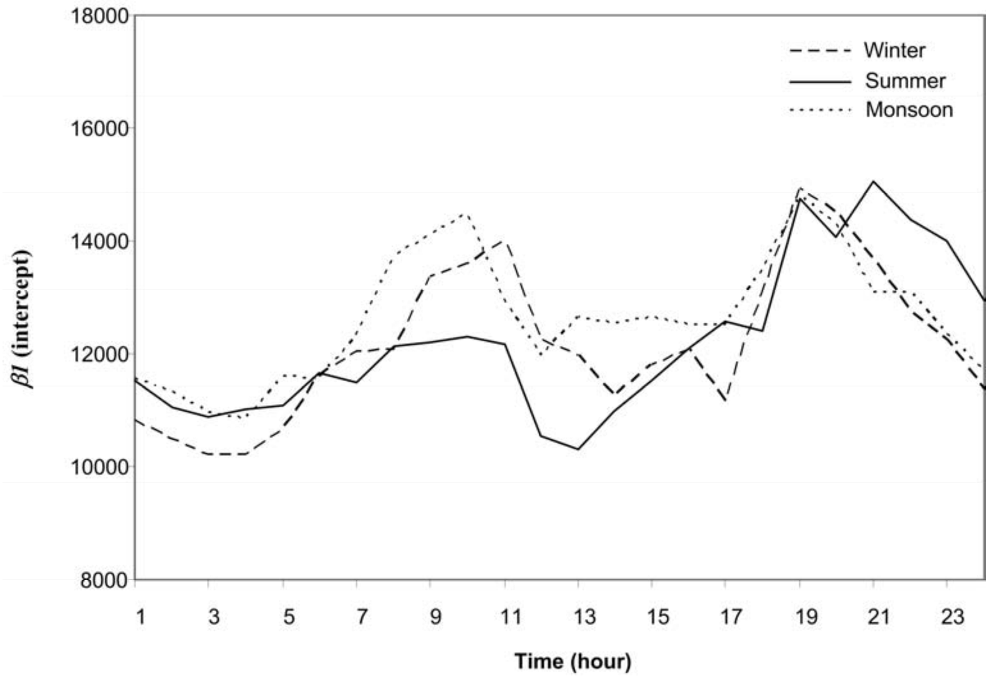

Figure 5.9: Daily variations in the β_1 coefficient over the seasons for weekdays.

Figure 5.10 shows the sensitivity of individual hourly demand (β_{CDH}) for each of the three month seasons as well as comparisons between actual and modelled daily demand profiles. The overall sensitivity is higher in summer (April) than in other months. It can be seen that the peak β_{CDH} sensitivity tends to coincide with or is close to the peak demand around midday. This is consistent with the higher temperatures during the working day when cooling of workplaces is needed. There is also a minor peak in sensitivity in the evening which coincides with people returning home and requiring cooling to reduce the heat accumulated during the day, particularly in summer. The coincidence implies that temperature rises from climate change will have a proportionally greater impact on peak demand levels.

Table 5.1 shows the detailed data for CDH sensitivity of demand (β_{CDH}) and measures of performance of the regressions for each of the time-slices in each season. The models indicate a reasonable fit with the actual demand with mean absolute percentage errors (MAPE) of 0.62-3.26% for January, 0.22-1.8% for April and 0.27-1.42% for July. These are backed up by high coefficients of determination (R^2) in most hours.

R^2 explains the proportion of the variance in demand that can be explained by the variance of CDH in that time-slice. It is not unreasonable that with demand being inherently variable, some periods particularly during the night when temperatures are lower and the relationship with CDH would be lower and would therefore possess low R^2. As such, the regression models appear to be able to provide a good indication of the relative sensitivity of each hour to changes in temperature.

To ensure that the 2004 data on which the monthly models was a reasonable basis for projecting demand into the future a series of comparisons with regression models trained on data from 2002 and 2003 were carried out 2004 regressions were 'normal' particularly with regards to the sensitivity coefficient. Figure 5.11 shows the daily profile of sensitivity coefficient β_{CDH} for each season for 2004 compared direct against the direct equivalent for 2002 and 2003. The monsoon pattern is almost identical across the three years but there is more of a spread for winter and summer. In saying that the 2004 trace is mainly inside the bounds of the other two and to a large extent there is a similar pattern across the day in all three years. The largest difference would be for the sensitivity of late afternoon/early evening in summer 2002 which is significantly higher than the other two years. The agreement between them indicates that the use of regressions from a single year is broadly representative of the other years. Detailed figures on the hourly performance in 2002 and 2003 (similar to Table 5.1) is given in the appendix. Overall, it appears that the demand sensitivity coefficient is related to demand levels. As such, an elegant refinement of the model would be to link β_{CDH} directly to time of day; this is an area for further work.

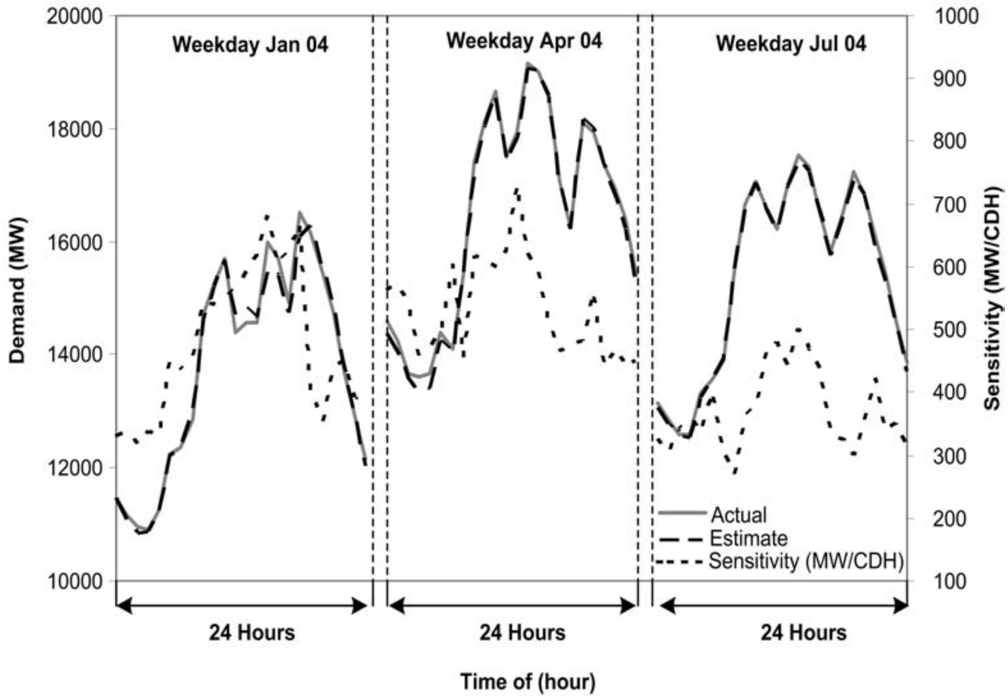

Figure 5.10: Seasonal average actual and estimated daily demand profiles for weekdays in 2004.

Time of day	Winter (January)			Summer (April)			Monsoon (July)		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	330	0.40	1.11	564	0.76	1.62	325	0.97	1.17
1	337	0.70	1.00	574	0.73	1.80	305	0.78	1.08
2	317	0.60	1.04	540	0.75	1.62	340	0.75	1.13
3	339	0.71	0.93	459	0.67	1.73	360	0.73	1.28
4	332	0.70	1.00	472	0.71	1.67	336	0.65	1.41
5	450	0.75	1.10	494	0.64	1.55	400	0.66	1.24
6	434	0.89	0.62	604	0.61	1.52	303	0.75	0.71
7	455	0.70	0.97	455	0.76	0.43	270	0.9	0.36
8	545	0.51	1.56	618	0.66	0.87	360	0.85	0.41
9	540	0.50	1.69	610	0.72	0.78	378	0.89	0.37
10	553	0.50	1.75	600	0.85	0.65	468	0.9	0.43
11	567	0.70	1.39	625	0.87	0.60	480	0.89	0.46
12	595	0.30	1.96	730	0.88	0.61	442	0.91	0.34
13	618	0.30	1.89	623	0.85	0.50	500	0.92	0.33
14	680	0.50	2.06	592	0.87	0.45	469	0.89	0.39
15	606	0.70	2.08	511	0.82	0.49	434	0.94	0.27
16	625	0.70	1.54	467	0.95	0.22	335	0.8	0.45
17	668	0.90	3.26	472	0.84	0.41	325	0.82	0.43
18	400	0.45	0.91	483	0.78	0.65	300	0.81	0.36
19	354	0.71	0.86	560	0.87	0.47	352	0.79	0.41
20	440	0.67	1.48	441	0.74	0.98	422	0.74	0.58
21	450	0.55	1.04	470	0.71	1.30	342	0.64	0.81
22	390	0.72	1.76	440	0.7	1.49	350	0.61	1.00
23	380	0.40	1.78	451	0.66	1.56	309	0.62	1.42

Table 5.1: Predicted regression coefficients and performance by season on weekdays.

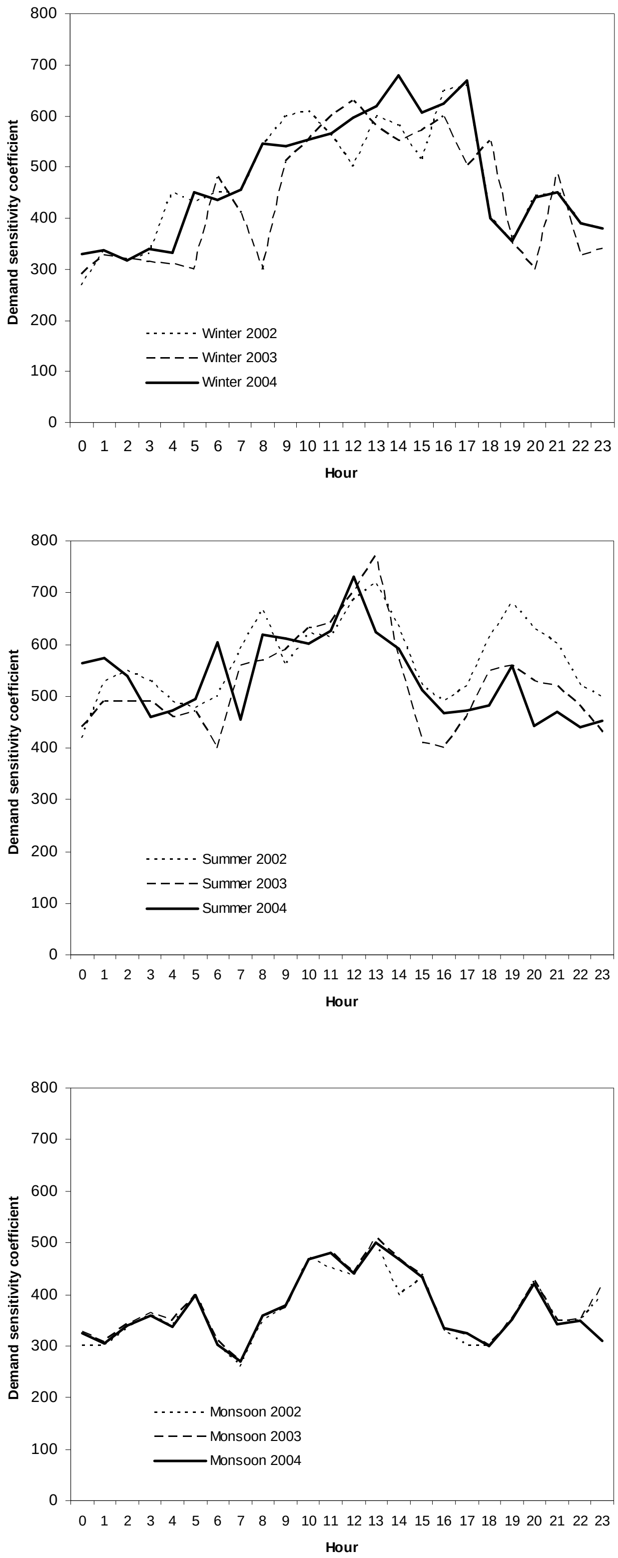

Figure 5.11: Comparison of demand sensitivity coefficient β_{CDH} for winter (top), summer (middle) and monsoon (bottom) for 2002, 2003 and 2004.

5.3.2 Weekends

Although there are differences between Saturday and Sunday demand profiles, the demand is typically much lower and consequently less detail was considered necessary to model them and they were treated jointly. Figure 5.12 shows the sensitivity of individual weekend hours (β_{CDH}) across the three seasons. Again the highest sensitivities tend to be in the middle of the day. Table 5.2 shows that the April (summer) sensitivity values exceeds those for weekdays shown in Table 5.1. The relative sensitivity of demand to temperature level is consistent with the higher temperatures when private companies still work on Saturday and people spend more time indoors increasing demand. On Sunday people tend to spend more time outdoors and demand and consequently temperature sensitivity picks up again when they return home. The difference between Saturday and Sunday and the relatively smaller dataset (typically 8 days per month) are responsible for the model performance being less good than for weekdays: the MAPE covers 0.58-4.34% for January, 0.07-0.81% for April and 1.55-7.28% for July and some hourly R^2 values are very low indeed. With demand much lower at weekends this poorer performance would not be expected to invalidate conclusions regarding peak demand change.

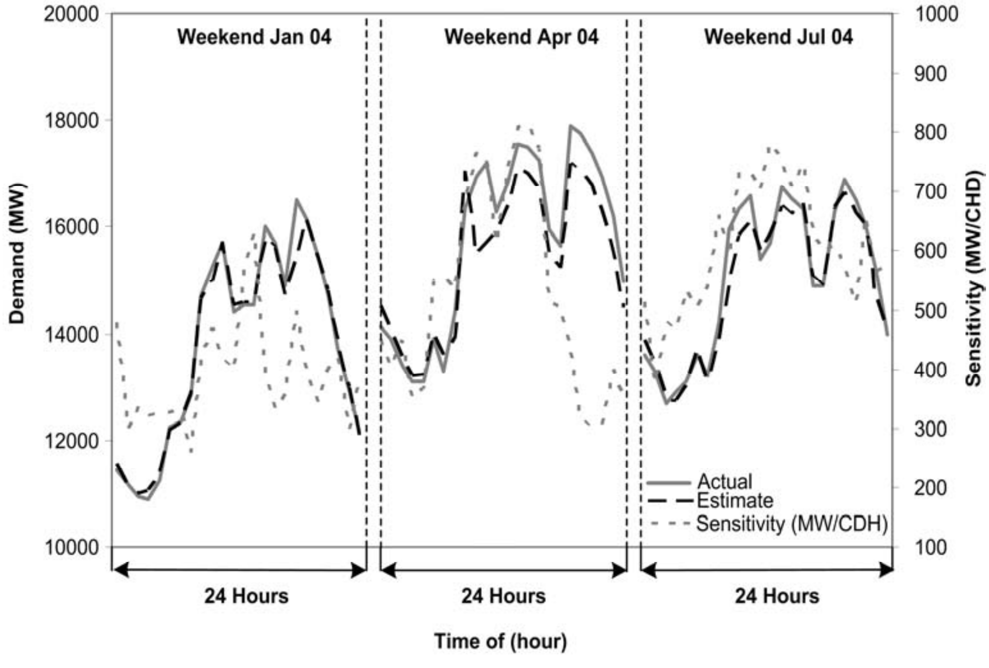

Figure 5.12: Seasonal average actual and estimated daily demand profiles and demand sensitivity for weekends in 2004.

Time of day	Winter (January)			Summer (April)			Monsoon (July)		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	480	0.55	1.65	452	0.60	1.80	513	0.60	3.10
1	300	0.52	1.12	405	0.70	1.35	377	0.50	2.97
2	337	0.41	1.37	450	0.75	0.72	479	0.70	2.25
3	321	0.39	1.67	351	0.67	0.79	467	0.78	1.82
4	327	0.61	1.85	368	0.66	0.67	534	0.80	1.55
5	328	0.52	1.02	550	0.81	0.97	503	0.80	1.67
6	333	0.41	1.07	557	0.61	2.31	539	0.80	1.74
7	260	0.38	0.63	537	0.64	5.30	660	0.60	3.89
8	420	0.32	1.02	689	0.10	7.71	592	0.43	6.99
9	470	0.34	0.73	766	0.10	9.62	732	0.32	7.22
10	420	0.34	0.94	760	0.06	9.43	731	0.30	7.28
11	400	0.41	1.06	613	0.20	6.99	704	0.51	4.02
12	570	0.62	0.88	737	0.20	7.45	783	0.60	3.88
13	630	0.46	1.09	809	0.20	8.17	751	0.40	6.92
14	400	0.42	0.70	816	0.20	8.10	708	0.35	6.83
15	333	0.52	0.65	773	0.18	7.79	748	0.42	5.97
16	360	0.35	0.94	515	0.12	6.03	629	0.47	3.85
17	500	0.35	3.03	505	0.09	5.50	599	0.60	2.72
18	399	0.34	4.34	431	0.07	4.70	610	0.55	2.29
19	345	0.53	0.58	316	0.07	3.91	576	0.68	2.07
20	400	0.23	1.47	300	0.08	3.70	512	0.61	2.26
21	420	0.31	1.42	307	0.08	3.76	658	0.75	2.02
22	300	0.12	1.98	400	0.14	4.03	563	0.57	2.92
23	382	0.20	1.92	352	0.12	4.08	579	0.63	2.41

Table 5.2: Predicted regression coefficients and performance by season for weekends.

5.3.3 Public Holidays

Figure 5.13 illustrates the 24 hourly mean demand and temperatures for the three seasons as well as the demand estimated by regression for public holidays. It can be seen that the peak sensitivity tends not to coincide with the peak demand in winter and monsoon. Like weekends, public holidays have significantly higher sensitivity of demand level to CDH. The differences in timing and duration of public holidays together with their low frequency mean that the model performance is generally poor, although the figures for July show good performance (Table 5.3). Mean absolute percentage errors for individual time slices are 3.73-17.90% for January, 4.50-14.86% for April and 0.27-1.421% for July.

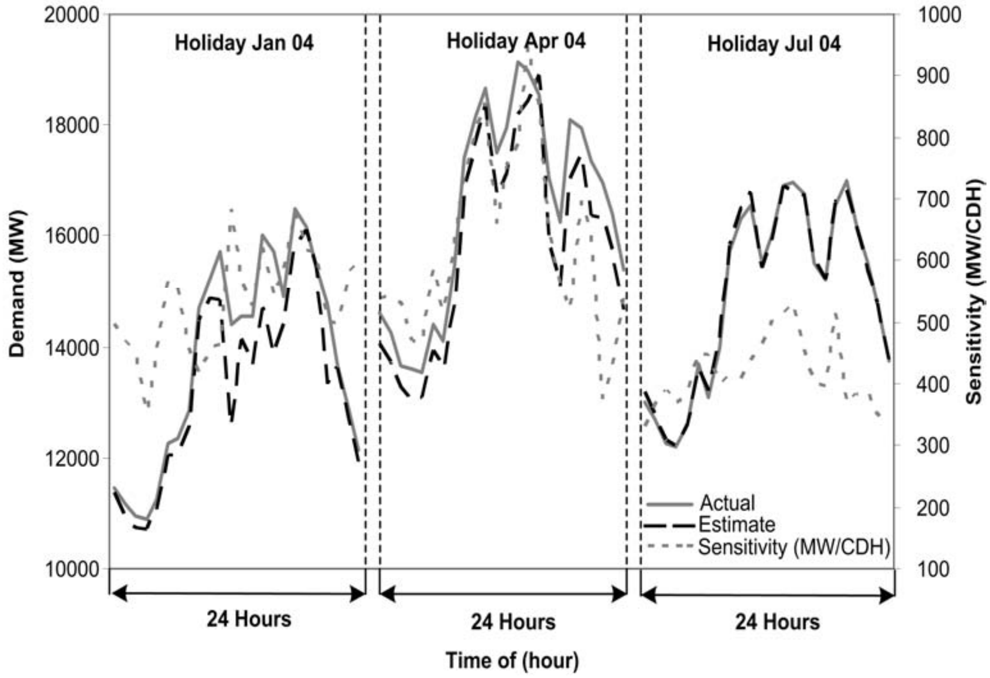

Figure 5.13: Mean actual and estimated demand and demand sensitivity in holiday during winter, summer and monsoon from 2004 in Thailand.

Time of day	Winter (January)			Summer (April)			Monsoon (July)		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	497	0.12	4.04	538	0.34	4.72	325	0.97	1.17
1	468	0.15	3.77	542	0.36	4.73	305	0.78	1.08
2	451	0.13	4.10	532	0.33	4.82	340	0.75	1.13
3	355	0.13	4.38	470	0.32	4.47	360	0.73	1.28
4	451	0.13	4.13	466	0.30	4.49	336	0.65	1.41
5	570	0.16	4.32	587	0.23	5.43	400	0.66	1.24
6	556	0.08	4.59	517	0.07	7.77	303	0.75	0.71
7	455	0.21	6.16	631	0.04	10.93	270	0.90	0.36
8	415	0.02	5.87	737	0.03	13.19	360	0.85	0.41
9	458	0.02	6.96	810	0.04	13.90	378	0.89	0.37
10	465	0.05	9.40	856	0.04	13.99	468	0.90	0.43
11	684	0.03	17.89	660	0.02	12.72	480	0.89	0.46
12	567	0.07	8.75	754	0.03	13.37	442	0.91	0.34
13	525	0.15	7.15	791	0.02	14.86	500	0.92	0.33
14	620	0.14	7.68	950	0.04	14.05	469	0.89	0.39
15	542	0.24	7.45	850	0.04	13.45	434	0.94	0.27
16	584	0.14	6.46	647	0.05	10.54	335	0.80	0.45
17	645	0.19	5.95	560	0.05	8.77	325	0.82	0.43
18	616	0.13	3.77	521	0.08	7.10	300	0.81	0.36
19	611	0.09	3.73	697	0.08	6.49	352	0.79	0.41
20	503	0.09	3.83	640	0.08	6.63	422	0.74	0.58
21	500	0.19	3.79	375	0.10	6.23	342	0.64	0.81
22	576	0.19	4.63	429	0.12	6.71	350	0.61	1.00
23	600	0.15	4.81	547	0.09	6.59	309	0.62	1.42

Table 5.3: Predicted regression coefficients and performance by season on holiday.

5.4 Demand Sensitivity

The demand model can be applied to estimate how sensitive demand patterns are to temperature change. Sensitivity can be calculated based on simple uniform changes (e.g., 1 or 2°C) in hourly temperatures across the year. Many of the earliest climate change assessments applied such a technique but it is not a credible method as future temperature changes will vary throughout the year and the diurnal temperature range will also alter which suggests non-uniform changes on a daily basis. However, for the purpose of illustration it is a valid exercise. The weather sensitivity model provides the basis for a more sophisticated and credible approach that is defined and examined in Chapter 6.

For each month, hourly temperatures were raised by 1 or 2°C. The impact on monthly peak and mean demand across the year is shown in Table 5.4. It shows that for a temperature rise of 1°C, average peak monthly demand increases between 1.4 to 4.6%. Monthly mean demand increases by 1.6 to 3.8% with the same rise. In most months the change in peak demand exceeds that of mean demand but there are a few exceptions such as November and December. March (summer) has the highest sensitivity coefficients and correspondingly sees the largest increase in demand for the 1°C temperature rise.

The sensitivity and increases associated with demand for July (monsoon) and January (winter) are smaller. The demand changes with the 2°C rise are approximately double that for 1°C but this is not always the case, particularly in the colder months. For example, for an hour where the historic temperature is 22°C, temperature rise would only add to the CDH count when a 2°C rise is applied to reach the 24°C threshold. When this happens, demand is increased by a proportionately greater amount.

Table 5.5 shows the impact of these changes in absolute, MW, terms based on the demand level in 2004. For example, for a temperature rise of 1°C in March (summer) the highest demand is 810MW (peak) and 577MW (mean) and for 2°C temperature rise with the doubling of demand increases are 1620MW (peak) and 1155MW (mean).

Figure 5.13 shows the impact on daily demand profiles for the 1 and 2°C temperature rise. The larger increases in demand at peak times can be seen in each case and is particularly clear for March.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Peak +1°C	4.2%	3.5%	4.6%	3.4%	4.3%	2.3%	2.8%	2.9%	2.8%	2.9%	1.4%	1.4%
Mean +1°C	3.5%	3.1%	3.8%	3.3%	3.6%	2.3%	2.4%	2.7%	2.4%	2.6%	1.6%	1.6%
Peak +2°C	8.4%	7.0%	9.3%	6.7%	8.8%	4.6%	5.7%	5.8%	5.8%	5.9%	2.7%	2.8%
Mean +2°C	6.9%	6.2%	7.6%	6.6%	7.1%	4.7%	4.8%	5.4%	4.8%	5.3%	3.2%	3.2%

Table 5.4: Percentage change in monthly peak and mean demand with uniform rise in temperature over year.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Peak +1°C	618	585	810	623	770	398	500	510	505	510	241	238
Mean +1°C	475	446	577	519	568	358	371	411	376	403	246	254
Peak +2°C	1236	1170	1620	1246	1589	796	1000	1020	1010	1000	482	480
Mean +2°C	950	893	1155	1052	1136	716	742	830	753	805	484	476

Table 5.5: Absolute change in 2004 monthly peak and mean demand (MW) with uniform rise in temperature.

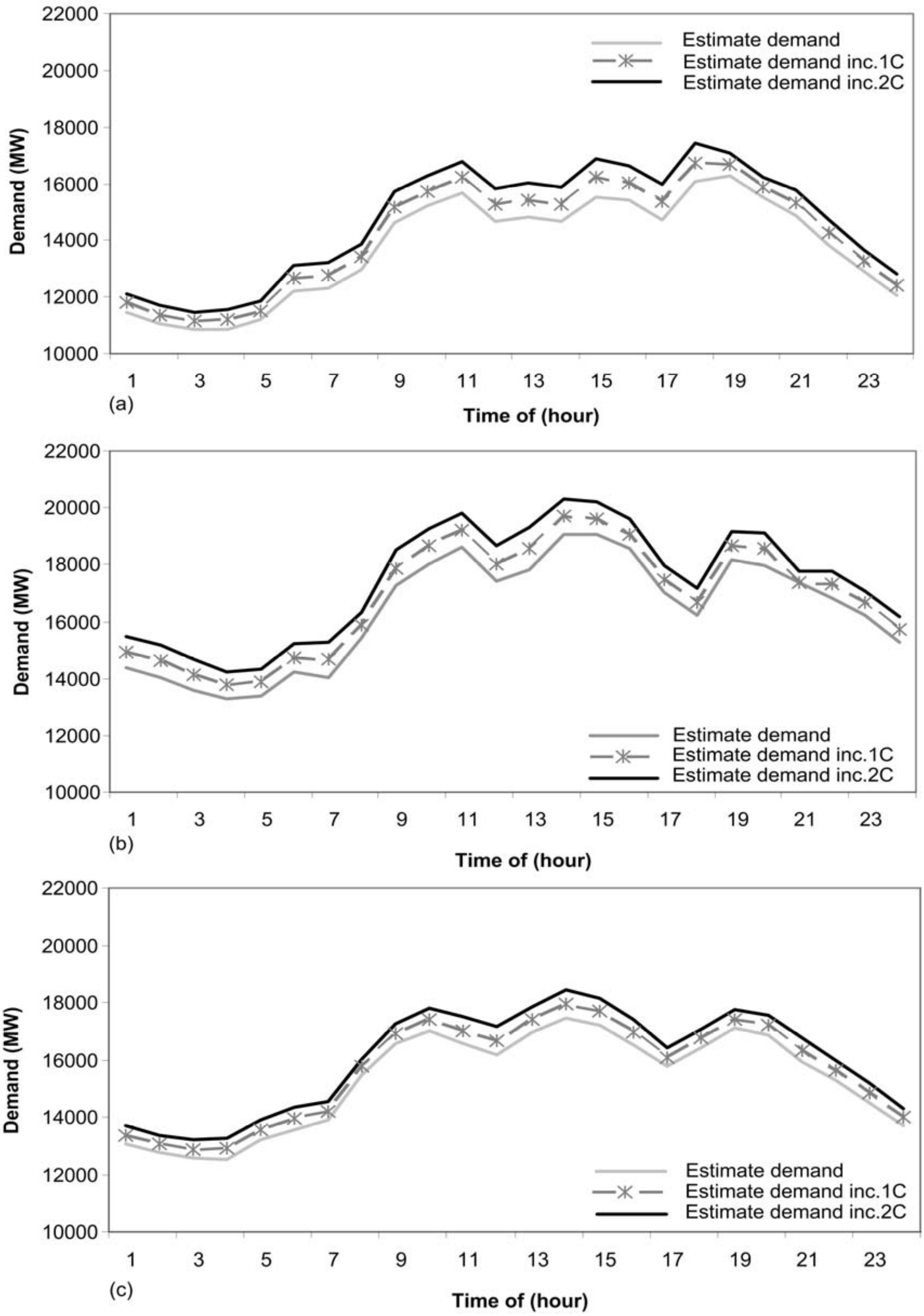

Figure 5.14: Modelled demand with uniform temperature rise of 1°C and 2°C in 2004, (a) winter (January), (b) summer (March) and (c) monsoon (July).

5.8 Chapter Summary

This chapter presented and assessed the options for modelling demand. It examined the requirements for projecting changes in demand with increasing temperature in Thailand. It presented a relatively simple weather sensitivity model that was based on sets of linear regressions relating demand in given hourly time-slices to cooling degree hours. The effectiveness of the approach in reproducing historic demand patterns was also assessed. Finally, the sensitivity of each model to rising temperature was examined using uniform temperature rises. The weather sensitivity model provides the basis for a more sophisticated and credible approach that is defined and examined in the next Chapter.

Chapter 6

Projecting Realistic Changes in Electricity Demand

This chapter builds on Chapter 5 by introducing how the weather sensitivity model can be used to create credible projections of how climate change may affect Thailand's daily, seasonal and long-term electricity demand. The temperature projections from the UK Hadley Centre climate model are used to assess hourly sensitivity to changes in mean and diurnal temperature. This is combined with socio-economic modelling results from the IPCC Special Report on Emission Scenarios (SRES) (Nakicenovic and Swart, 2000) to project relative and absolute changes in Thailand's electricity demand.

6.1 Modelling Realistic Changes in Demand

While the modelling approach in Chapter 5 illustrates the sensitivity of individual months to uniform changes in temperature, this in itself does not offer a defensible approach for projecting realistic changes in demand. However, the weather sensitivity model provides a mechanism for doing so by making use of the relative (percentage) change in demand for a given change in temperature. With demand rising in future, it is important for system planners to be able to project absolute (MW) changes in demand. A process was required for estimating future climate-induced demand changes that were consistent with socio-economic and climate model scenarios.

With both greenhouse gas emissions and electricity demand ultimately driven by the same socio-economic and technological patterns, it was necessary to construct a series of linked components to capture these effects. As Figure 6.1 shows, a given scenario of economic and population growth gives rise to a particular pattern of greenhouse gas emissions. The emissions scenarios drive a climate model which provides estimates of changes in temperatures. These are then added to the historic temperature series to create a scenario of future temperature. The demand sensitivity model developed in

Chapter 5 then converts the temperatures into demand. The normalised changes (relative to historic demand) are converted into MW demand changes by projecting future demand levels from the historic level at growth rates derived from the same socio-economic scenario (GDP and population). Each of the stages are outlined below.

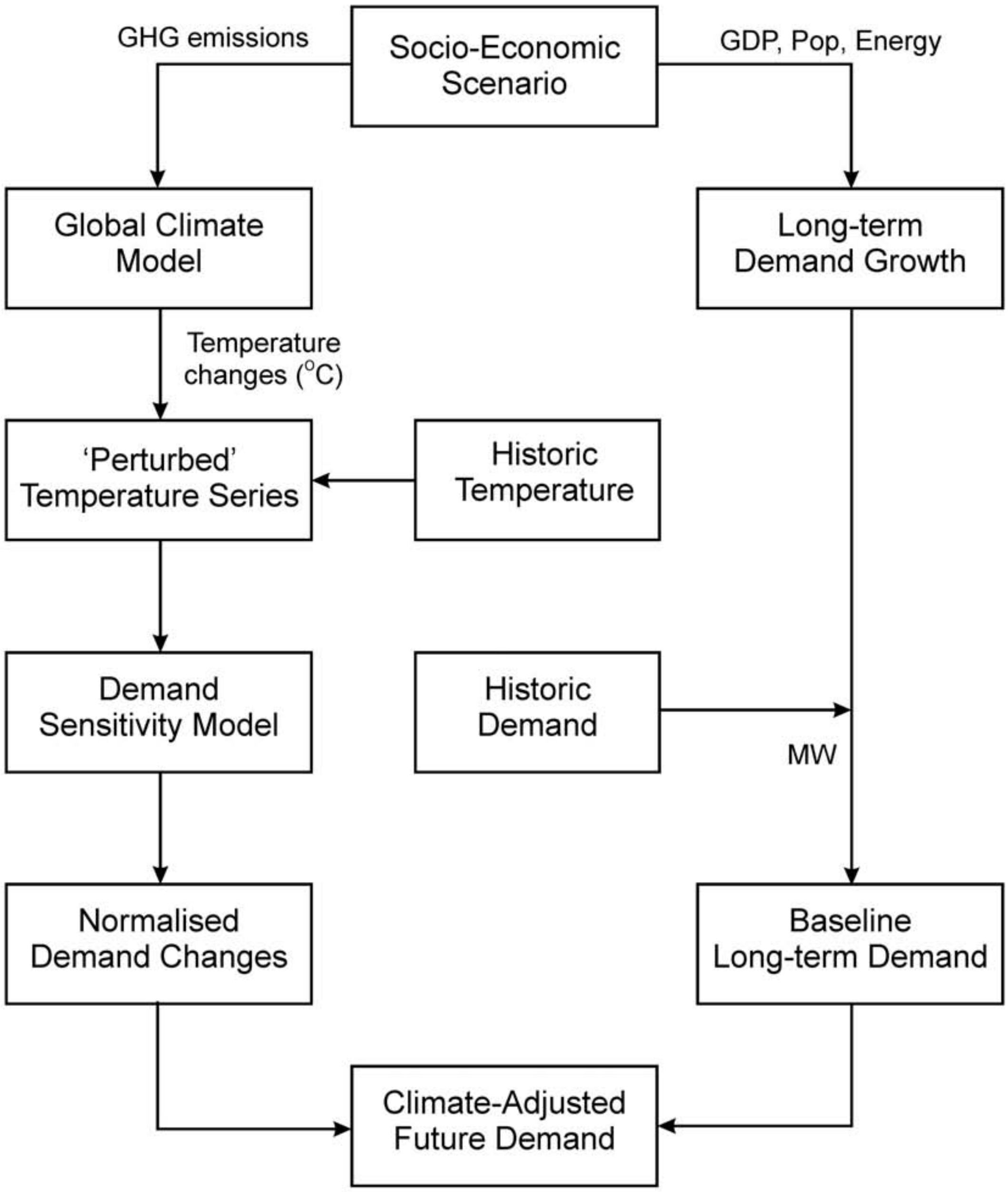

Figure 6.1: Process for estimating future climate-induced demand changes.

6.1.1 Long-Term Socio-Economic Scenarios

As highlighted in Chapter 2, (section 2.3.3) the IPCC Special Report on Emission Scenarios (SRES) detailed a serious of greenhouse emissions scenarios suitable for simulation in climate models as well as in impact assessments. For each storyline, different scenarios (e.g. A1, A2, B1 and B2) were developed for the SRES using six representative Economy-Energy-Environment (EEE) models to capture the current range of uncertainties of future greenhouse gas emissions that arise from different modelling approaches as well as uncertainties about the driving forces. A total of forty SRES scenarios were developed and each is regarded as equally valid. The results from the model runs are made available on the IPCC Data Distribution Centre (DDC) (IPCC 2007) website and consist of 10-yearly regional forecasts for population, GDP, energy use and production, broken down by fuel and land-use and greenhouse gas emissions.

6.1.2 Applying Climate Model Temperature Projections

Temperature projections for future periods are defined by General Circulation Models (GCMs), complex numerical models of the atmosphere and oceans that provide information on a wide range of climate variables. The transient GCM simulations used in the SRES are driven by GHG concentrations that vary with time: observed concentrations were used for the period from 1860 to 1990 with increases thereafter up to 2100 as defined by the GHG emissions scenario in question. To minimise the effects of bias within GCMs it has been common practice to use the 'perturbation' method rather than use GCM output directly. Perturbation adjusts historic values by the difference between GCM-modelled values for a future period and a baseline 'current' climate (typically 1961-1990). The future periods are generally 30 year averages corresponding to the 2020s (covering the years 2011-2040), the 2050s (2041-2070) and the 2080s (2071-2100). There are a wide range of GCMs under development at present. Each model has a different structure, spatial resolution and range of processes that are modelled. These give rise to different climate outcomes, although there is reasonably good agreement in temperature trends. The SRES therefore used several GCMs with the same GHG trends to capture model variability.

Early assessments of climate impacts applied simple changes in daily temperatures. A more sophisticated approach is to capture the changes in diurnal temperature range. To do this three temperature variables are required: changes in the mean ($\Delta TMEAN$), maximum ($\Delta TMAX$) and minimum ($\Delta TMIN$) temperatures. The IPCC DDC (IPCC 2007), provides mean monthly temperature changes for each of these variables. A method termed as 'morphing' was developed by Belcher et al. (2005) to produce design weather data for building thermal simulations that accounts for future changes to climate. Morphing combines present-day observed historic temperature series by the amounts implied by the GCM. The morphing technique provides a vertical shift in mean temperatures and stretches the range of values by the change in diurnal temperature range. This aims to capture changes in the mean and variance in temperatures. For each hour, the climate change adjusted temperature, T_{cc}, is given by (Belcher et al., 2005):

$$T_{cc} = T_{act} + \Delta TMEAN + \alpha(T_{act} - t_{mean}) \tag{6.1}$$

where T_{act} is the historic temperature in the base year and t_{mean} was the historic average daily temperature in that month. The scaling factor, α adjusts temperatures by the relative change in diurnal temperature range:

$$\alpha = \frac{(\Delta TMAX - \Delta TMIN)}{(t_{\max} - t_{\min})} \tag{6.2}$$

where $\Delta TMAX$ and $\Delta TMIN$ are the respective changes projected for mean monthly maximum and minimum temperatures, and $t_{\max}$ and $t_{\min}$ are historic mean monthly maximum and minimum temperatures (°C).

The altered temperature profile is applied to the demand sensitivity model to provide an estimate of demand levels at elevated temperatures. These are compared with the original modelled demand to indicate the normalised demand changes.

6.1.3 Socio-Economic Changes and Long-Term Demand Growth

The absolute demand changes implied by climate change require realistic baseline estimates of future demand levels. As long-term demand growth is driven by GDP and population size, a common approach has been to devise correlations using regressive models (e.g., Mohamed and Bodger, 2005; Al-Iriani, 2005) such as:

$$D_t = \beta_1 + \beta_2 (G_t - G_{t-1}) + \beta_3 (P_t - P_{t-1}) + \varepsilon \tag{6.3}$$

where G is GDP, P is population size and the subscripts t relate to the current year and $t\text{-}1$ to the previous year.

One of the difficulties of regressive methods is that they do not explicitly consider structural or technical changes or economic factors that influence choices (e.g., relative fuel prices). These effects are, however, accounted for in the Economy-Energy-Environment models used in the SRES. The models produce energy consumption estimates for fuels including electricity (in Exajoules, EJ) at 10 year intervals. It is possible to extract the energy growth rates consistent with GDP, population and GHG emissions and use them to inflate power demand. This requires assumptions to be made regarding the relationships between average (energy) demand and peak demand. Here a constant load factor has been assumed into the future. The baseline demand is combined with the normalised changes to estimate the absolute changes in demand implied by climate change.

With the SRES developing 40 socio-economic scenarios implemented by six modelling groups and applied to at least six GCMs there are a very large number of possible scenarios to consider. Clearly it is beyond the scope of this work to explore the range of potential electricity demand outcomes implied by the full set of SRES and GCM scenarios. However, a subset of them has been assessed to illustrate the potential changes. To ensure consistency between socio-economic assumptions between each storyline only one of the SRES EEE models has been applied here.

The Asian Pacific Integrated Model (AIM) was developed by the National Institute of Environmental Studies in Japan (Morita et al., 1994). It is a large-scale simulation model for scenario analyses of emissions and the impacts of global warming in the Asian-Pacific region. Although able to produce global estimates, there is greater detail and emphasis for the Asia-Pacific zone. The model groups similar countries together and assumes that development progresses at the same rate across the region. As such, the growth rates applicable to the region containing Thailand should be broadly applicable to Thailand itself. As shown in Chapter 4 this a reasonable assumption.

The AIM model results from four scenarios were extracted from the IPCC DDC and cover the broad range of socio-economic possibilities across the four storylines (A1, A2, B1 and B2). Table 6.1 provides a sample of the socio-economic indicators and electricity growth rates for the decades up to 2020, 2050 and 2080. It is apparent that there are significant differences in Gross Domestic Product (GDP) and population growth rates throughout the century, particularly in later years. The divergence in scenarios means that while growth rates for electricity demand are broadly similar up to 2020 there are very large changes towards 2050 and beyond.

To allow annual forecasting of demand and comparison with other models the 10-yearly steps in electricity demand growth presented for the AIM model were converted into an equivalent annual growth for each decade. The decadal change in electricity consumption (EJ/year) was used along with the following equation:

$$g = \sqrt[n]{\frac{Ele_{10}}{Ele_0}} - 1 \qquad (6.4)$$

Here n is the number of years in the period (10), g is the equivalent annual compound growth rate of electricity demand (%/year), Ele_0 is the demand at the start of the decade (EJ/year) and Ele_{10} is the demand at the end.

The GDP, population and growth rates from the AIM scenarios are shown graphically in Figures 6.2 and 6.3 to 2100 and are summarised for key decades in Table 6.1. All show initially rapid economic, population and electricity demand growth that tends to slow over the century. It is apparent that there are significant differences in GDP and population growth rates, particularly in later years. In scenarios A1 and B1, population declines in the later stages of the century and B1 shows a reduction in electricity demand as a result.

Decade prior to	Indicator	AIM Scenario			
		A1	A2	B1	B2
2020	GDP	7.8	4.2	6.1	6.3
	Population	0.8	1.3	0.9	0.9
	Electricity	5.8	6.9	6.3	5.7
2050	GDP	4.5	1.7	4.3	3.1
	Population	0.1	0.5	−0.1	0.3
	Electricity	5.0	3.5	1.5	2.8
2080	GDP	2.4	4.2	2.0	1.6
	Population	−0.8	0.8	−0.7	0.1
	Electricity	2.3	1.8	−0.5	2.0

Table 6.1: Sample annual growth projections in percent (IPCC, 2007).

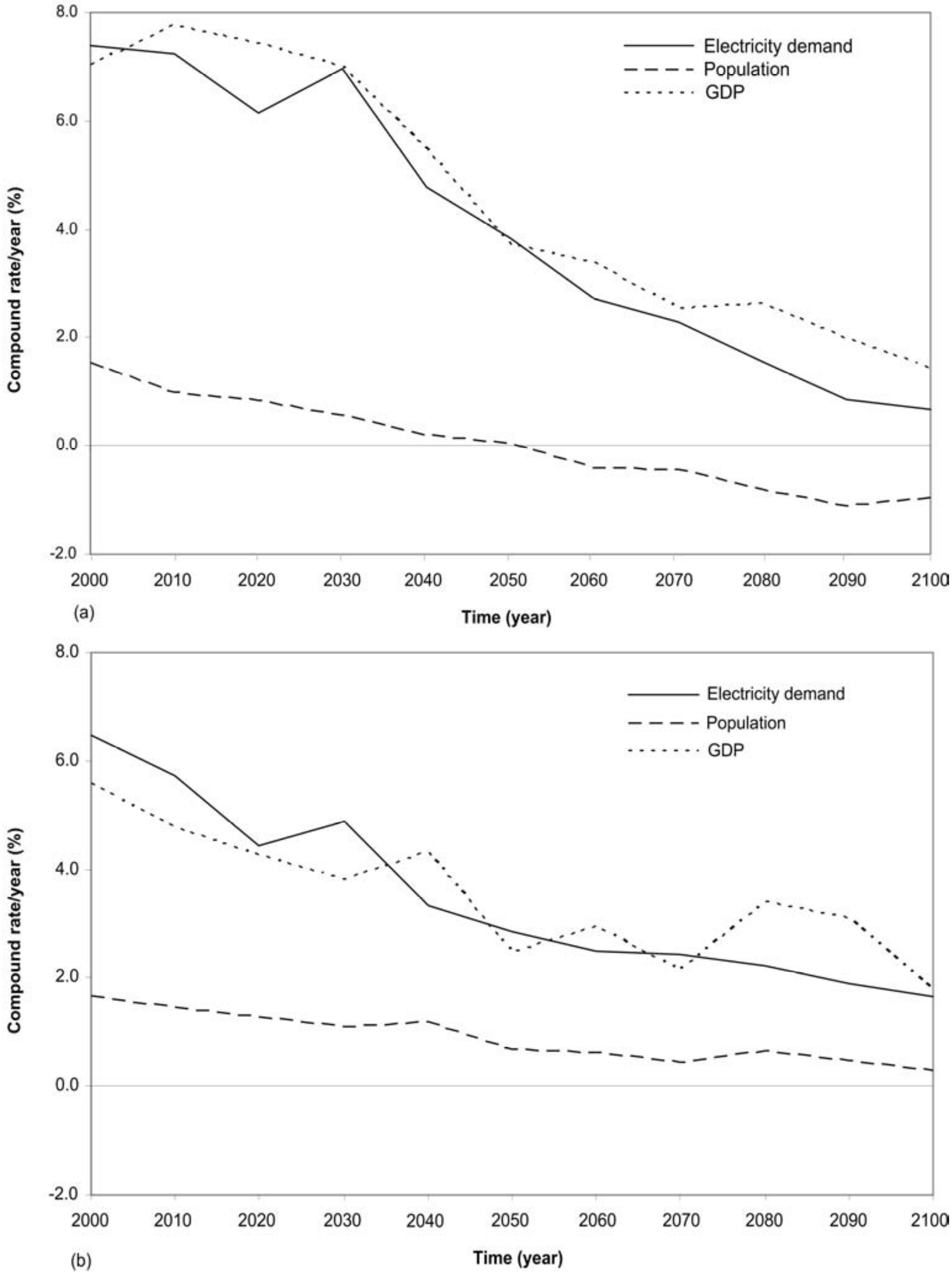

Figure 6.2: Annual growth rates for GDP, population and electricity demand over the period 2000 to 2100 for (a) A1, (b) A2 scenarios.

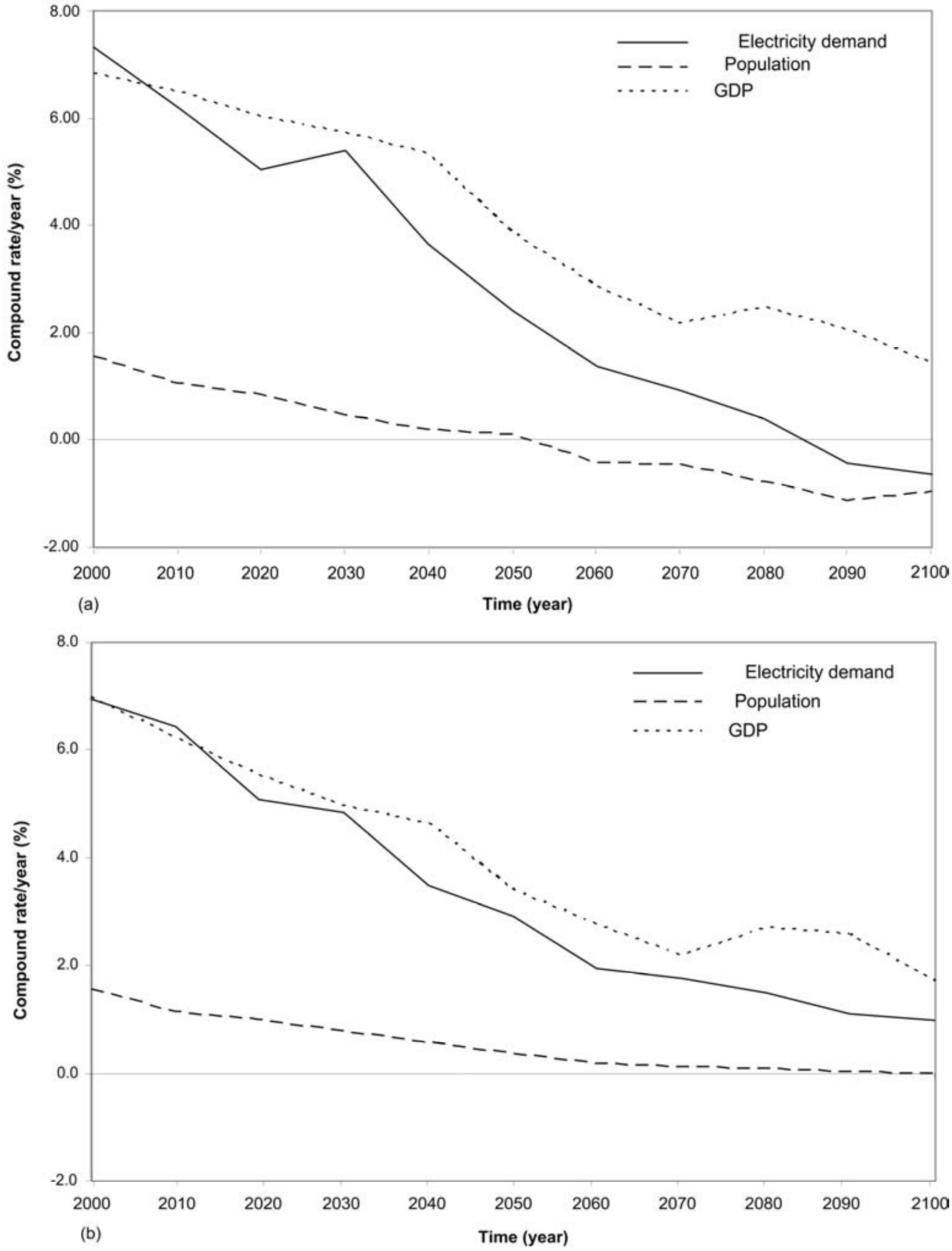

Figure 6.3: Annual growth rates for GDP, population and electricity demand over the period 2000 to 2100 for (a) B1, (b) B2 scenarios.

The divergence in scenarios means that growth rates in electricity demand are similar up until around 2020. There are very large changes towards 2050 and beyond. Application of the annual growth in electricity demand implied by each AIM scenario to the peak demand in 2004 results in the demand projections shown in Figure 6.4. The divergence between the scenarios can be seen clearly in part (b): in the year 2020 the spread of values is 8.7GW, in 2050 it is 70.2GW while in 2080 the spread is 320.5GW.

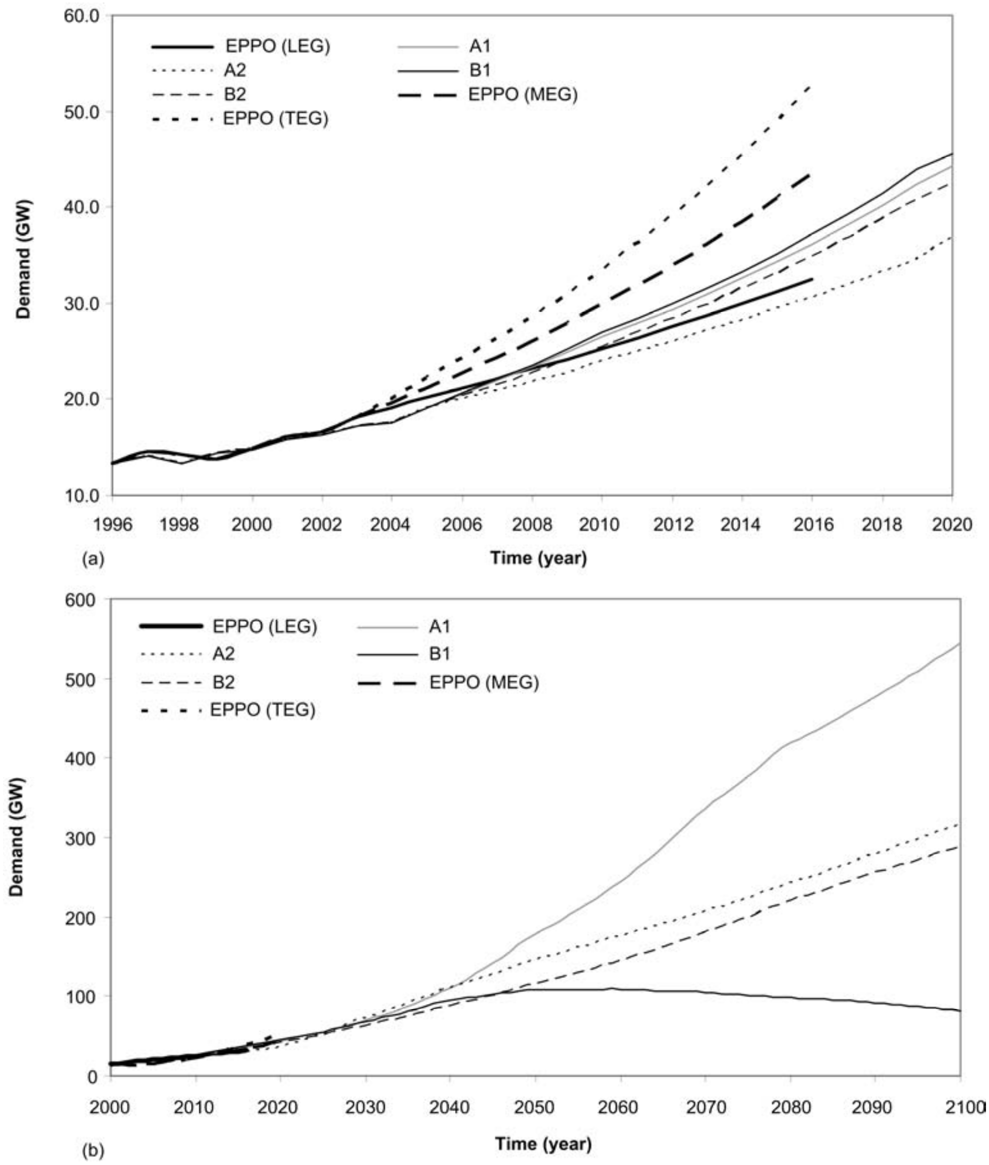

Figure 6.4: Projected demand for the 4 AIM scenarios and the 3 EGAT scenarios (a) projected demand from year 1996 to 2020; (b) projected demand 2000 to 2100.

Comparison with Other Forecasts

To check that the peak demand values calculated by inflating 2004 peak demand by AIM electricity growth rates were sensible, they were compared with two sets of growth forecasts based on simple regressive models. The first was the forecast to 2016 performed by the Thai utility EGAT for low, medium and target economic growth (LEG, MEG and LEG, as mentioned in Chapter 4) (EGAT 2004). These are clearly shown in Figure 6.4a with the lower growth estimates being similar to the AIM forecast results.

The second sets of forecasts were created with a regression model constructed by the author using historical Thai demand, GDP and population data for 1997 to 2004. The monthly model was developed from peak monthly demand and quarterly GDP and population data, which were linearly interpolated on a monthly basis. The model was calibrated on data from 2001 to 2004 and validated on data from 1997-2000. The performance of the model is shown in Table 6.2. The performance in the calibration period is very good but suffers when retrospectively applied to the earlier validation period (Figure 6.5). However, given that the earlier period includes that of the Asian economic crisis of 1998 its performance is reasonable.

The simple regression model was driven by the growth rates for GDP and population in the AIM projections. There was good agreement between the A1 scenarios but a poorer fit with B2. This perhaps reflects the fact that recent historical growth better matches the economically-driven development of the A1 scenario rather than the ecologically-driven scenarios which imply major structural changes. The comparison is shown in detail in Appendix B.

Performance	Calibration 2001-2004	Validation 1997-2000	Whole Period 1997-2004
R^2	0.97	0.66	0.94
MAPE (%)	2.47%	2.70%	2.58%
Mean error (MW/Month)	411	364	387

Table 6.2: Comparison of calibration and validation statistics.

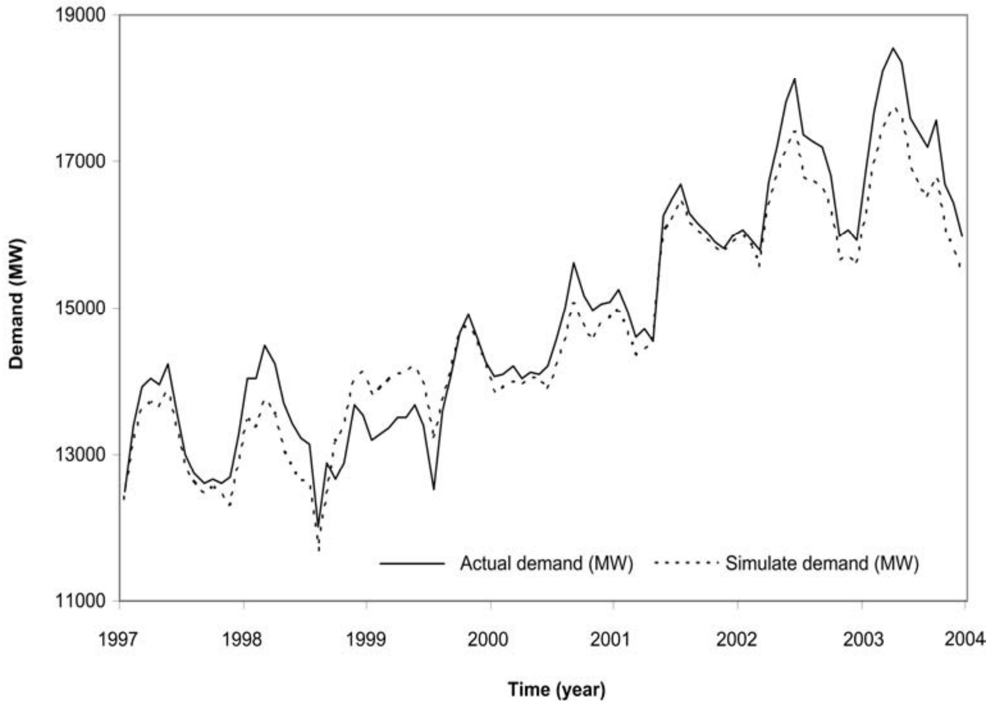

Figure 6.5: A comparison with actual and simulated demand between (validation from 1997-2000) and (calibration from 2001-2004).

6.2 Projections for Thailand

To illustrate the process of projecting changes in demand from temperature changes a single GCM has been used. The UK Meteorological Office Hadley Centre HadCM3 model (Gordon et al., 2000) has a spatial resolution of 2.5° latitude by 3.75° longitude. This requires 72 × 96 cells to represent the entire globe. Figures 6.6 to 6.8 show the world pattern of temperature change projected by the Hadley Centre GCM for the 2020s, 2050s and 2080s under the high emissions A1F scenario. The F defines a sub-scenario with particularly high fossil-fuel use. The figures show, global temperature rise across large land masses in all regions.

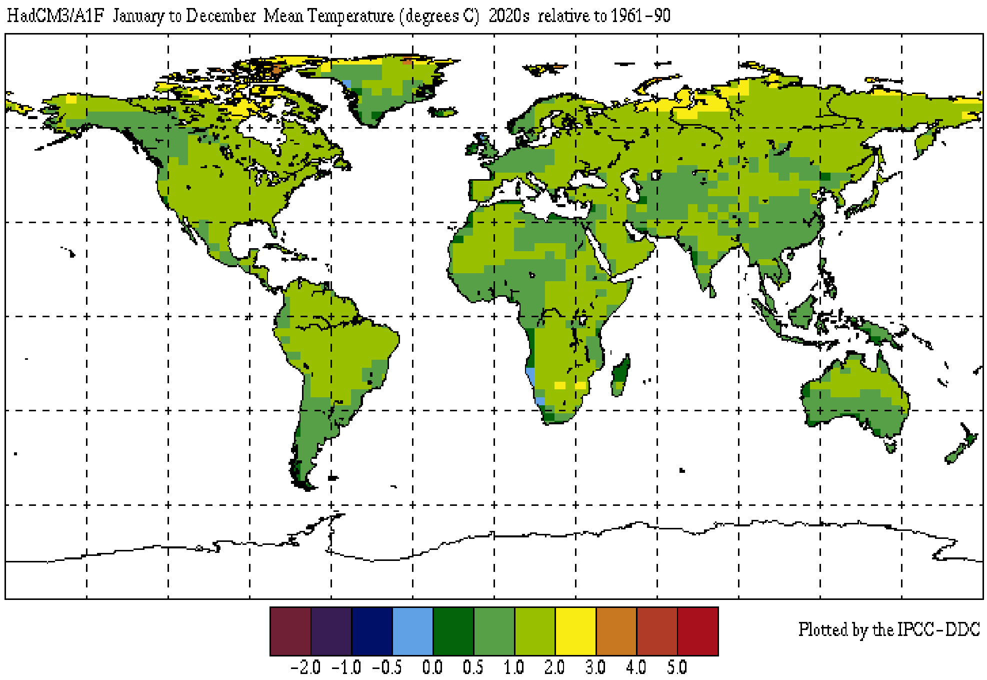

Figure 6.6: Annual mean temperature change (°C) for the 2020s with Hadley Centre GCM and A1F scenario.

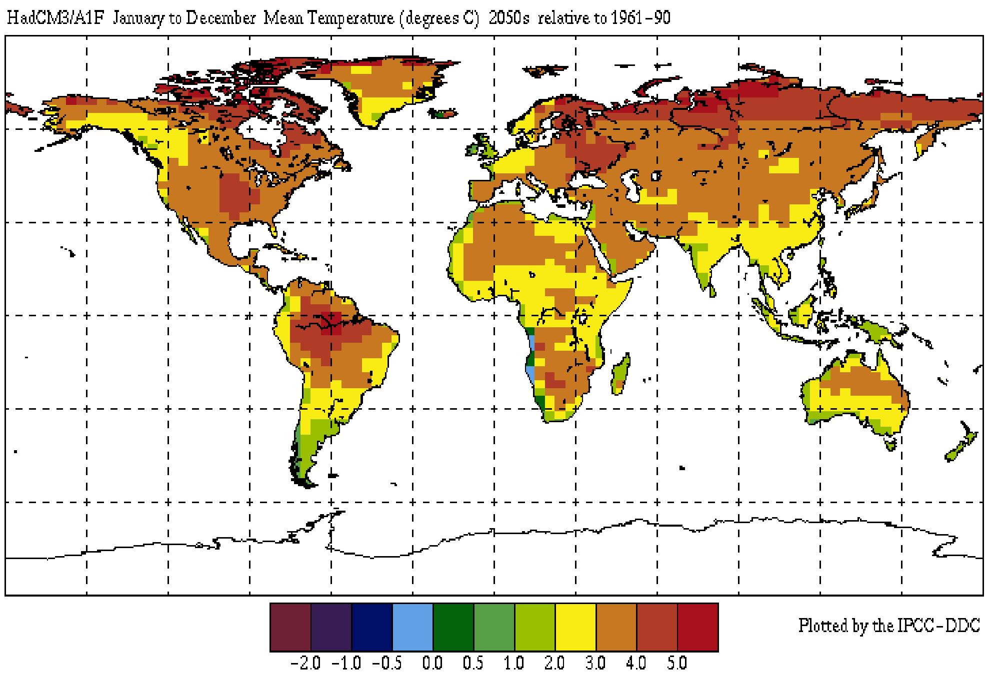

Figure 6.7: Annual mean temperature change (°C) for the 2050s with Hadley Centre GCM and A1F scenario.

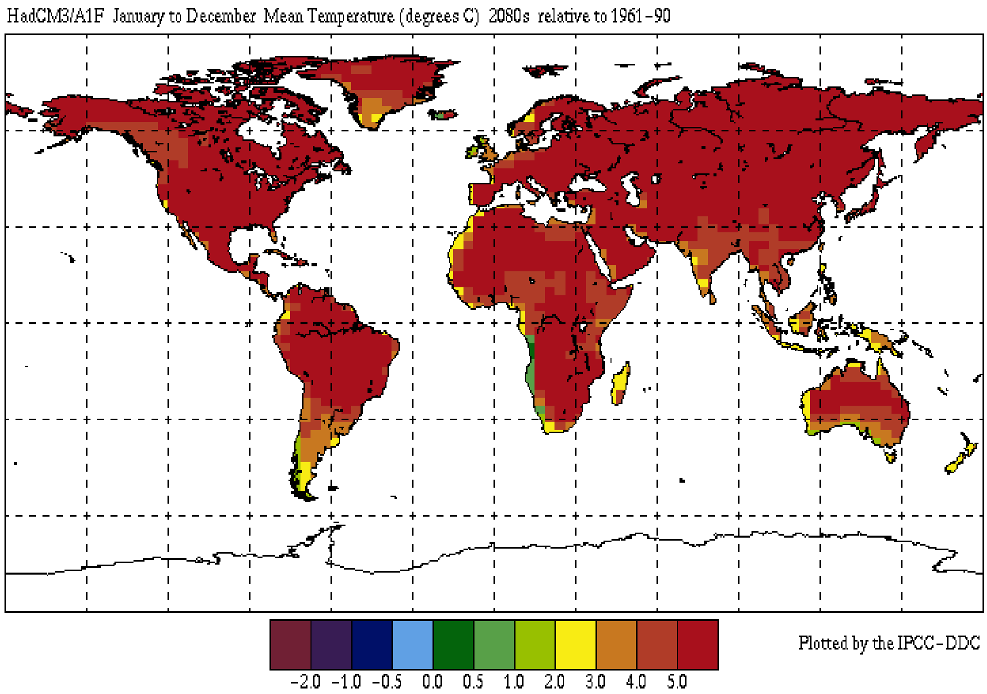

Figure 6.8: Annual mean temperature change (°C) for the 2080s with Hadley Centre GCM and A1F scenario.

The resolution of the Hadley Centre GCM means that only a few model cells cover Thailand. Figure 6.9 shows this. This presents a challenge for climate assessments to effectively and accurately translate the projections for large areas to local conditions through a process known as 'downscaling'. In this case this has not been a problem as the demand data is an aggregate for the whole country and only reliable meteorological data for the Bangkok area could be sourced. Of the four cells shown in Figure 6.9, cell 1 (top left) almost entirely encloses the Bangkok metropolitan area. The temperature change data for this cell alone was used to calculate changes in demand. This was considered reasonable given that the Bangkok area is responsible for 70% of Thai demand.

The change data is made available on the IPCC Data Distribution Centre in the form of interactive change maps for average monthly, seasonal and annual changes in mean, maximum and minimum temperatures. The monthly change fields for each variable were extracted from the maps for conditions in the 2020s, 2050s and 2080s and loaded into Excel spreadsheets for further processing. An example of the text files is shown for the B2a scenario (a sub-scenario of B2) in Figure 6.10 which shows the change in annual mean temperature by the 2080s relative to 1961-1990 mean. It also highlights the location of the four cells in Figure 6.9.

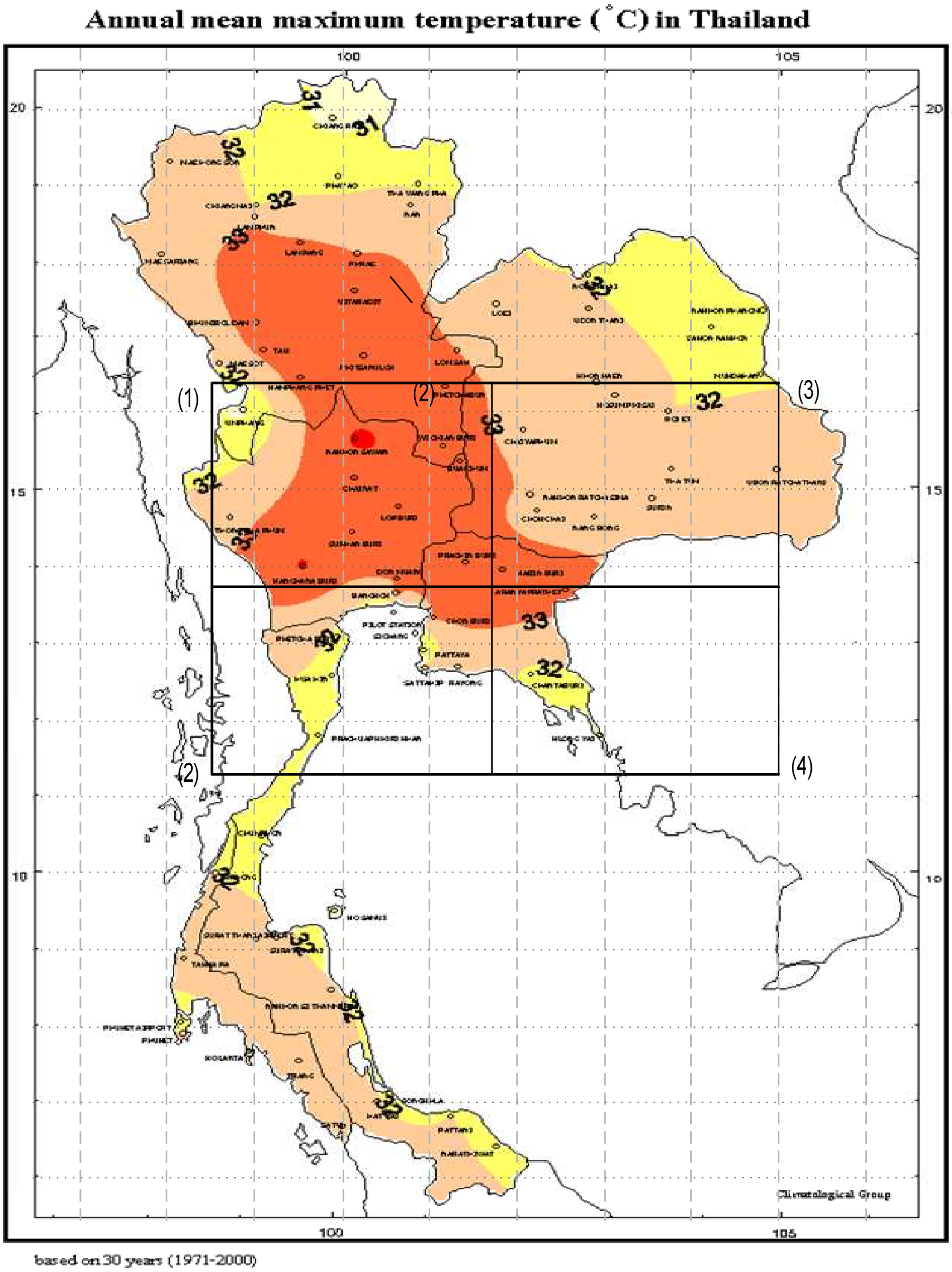

Figure 6.9: Map of Thailand shows the location of the 2.5° latitude by 3.75° longitude model cells for the Hadley GCM.

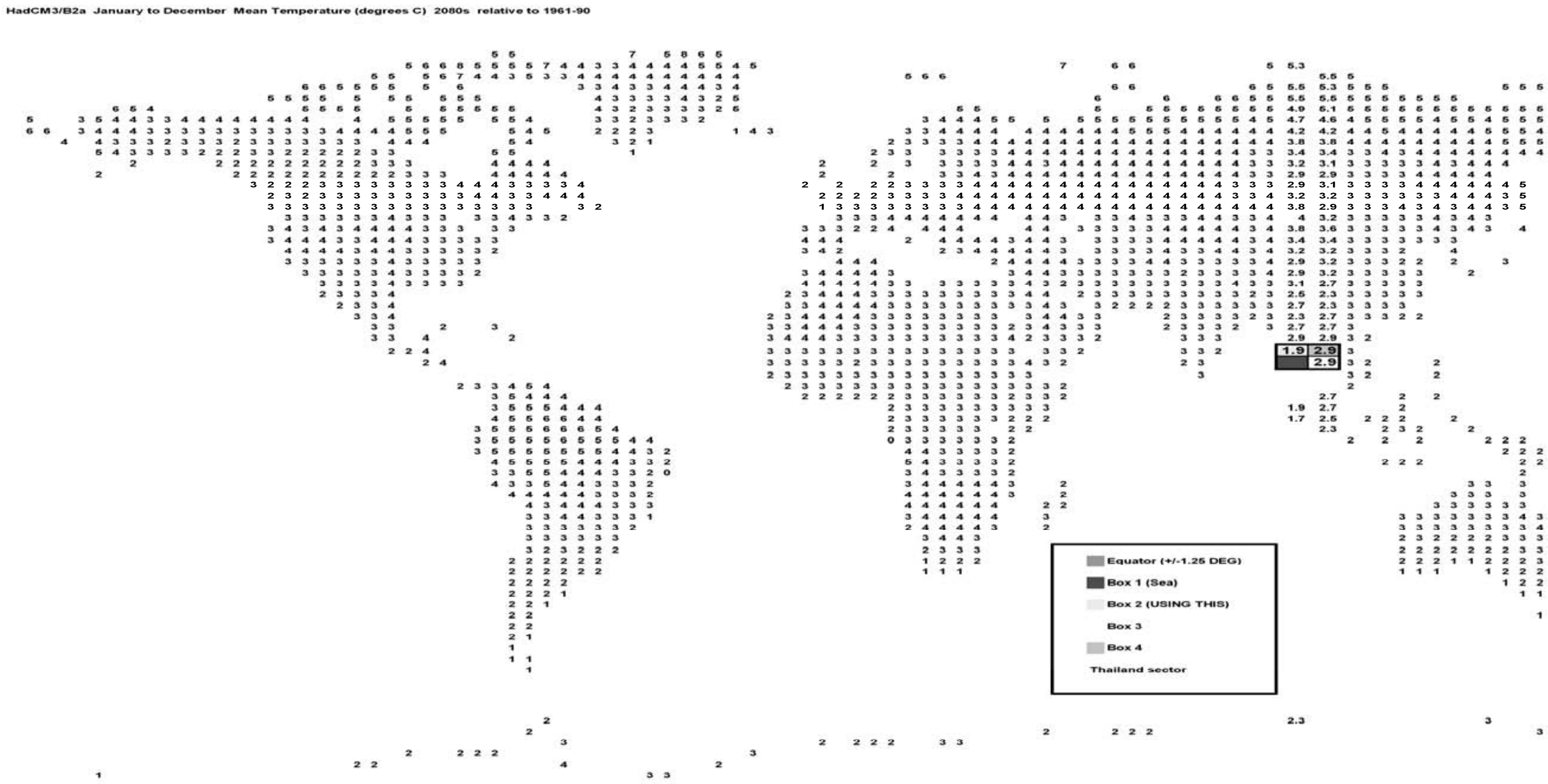

Figure 6.10: Structure of the temperature change data for the Hadley GCM showing the annual mean temperature change in the 2080s relative to the 1961-1990 mean (°C).

6.2.1 Temperature Changes for Thailand

The changes in temperatures projected by the Hadley Centre HadCM3 GCM are presented for the specific model grid cell. Table 6.3 shows average annual changes in maximum, minimum and mean daily temperature for the 2020s, 2005s, and 2080s for the four scenarios (A1, A2, B1 and B2). It can be seen from the table that the temperature rises reflects the development scenario with the higher emissions A1F scenario showing far more warming than the 'greener' scenarios. The range of increase in mean annual temperatures ranges from 0.62°C in 2020 to 1.74−3.43°C in 2080. In most cases the annual diurnal temperature range is projected to increase, as increases in maximum temperatures outstripping changes to the minimum.

The annual changes disguise significant seasonal differences. Figure 6.11 shows the projected seasonal changes in average monthly temperature from just the A2 scenario for the winter (January), summer (April) and Monsoon (July). It shows that by the end of this century the winter temperatures will rise more than summer and monsoon. Table 6.4 shows the detailed projected seasonal changes in maximum, minimum and mean temperature for the 2020s, 2050s and 2080s. Diurnal temperature range is seen to increase in summer and monsoon but mostly decrease in winter.

Model		Temperature rise from present (°C)		
Scenario	Variable	2020s	2050s	2080s
A1	Mean	0.62	1.93	3.43
	Max	0.67	1.78	3.62
	Min	0.66	1.88	3.50
A2	Mean	0.62	1.37	2.87
	Max	0.49	1.41	2.88
	Min	0.46	1.47	2.89
B1	Mean	0.62	1.18	1.74
	Max	0.49	1.22	1.78
	Min	0.46	1.27	1.67
B2	Mean	0.62	1.18	1.93
	Max	0.67	1.22	1.96
	Min	0.66	1.06	1.88

Table 6.3: Average annual changes in mean, maximum and minimum temperatures from Hadley Centre GCM.

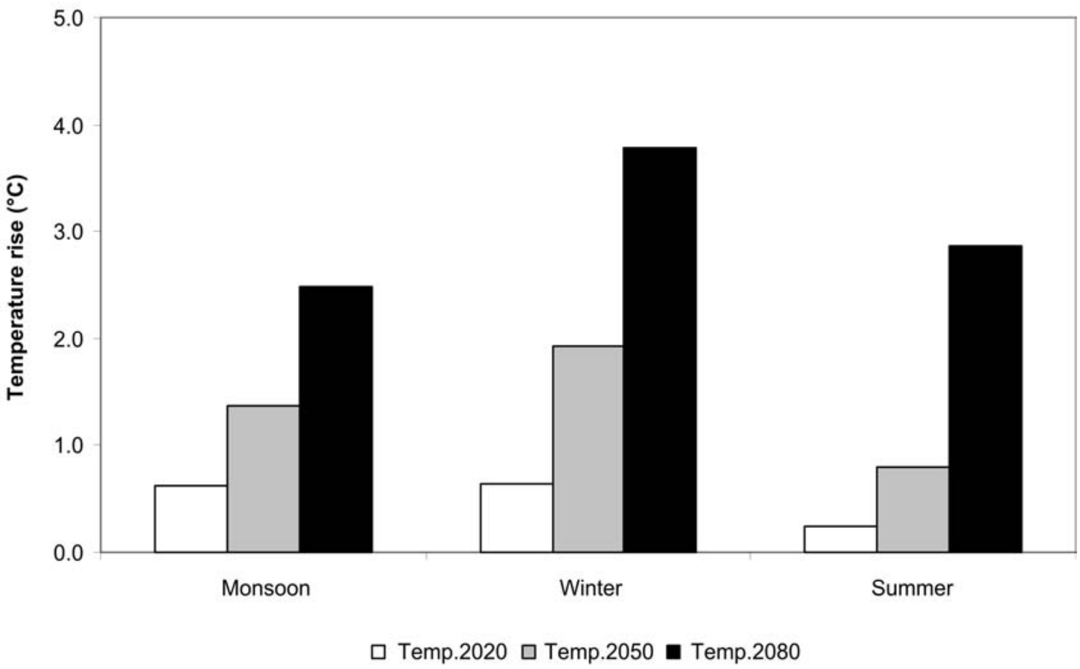

Figure 6.11: Seasonal changes in mean temperature from A2 2020s, 2050s and 2080s.

Model		Temperature rise from present (°C)								
Scenario	Season	2020s			2050s			2080s		
		Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
A1	Winter	1.00	1.04	1.06	2.30	2.33	2.28	4.55	4.54	4.52
	Summer	0.62	0.67	0.46	1.93	1.96	1.88	3.61	3.80	3.70
	Monsoon	0.62	0.67	0.66	1.56	1.59	1.47	2.87	2.88	2.69
A2	Winter	0.62	0.49	0.66	1.93	1.96	1.88	3.80	3.80	3.91
	Summer	0.25	0.30	0.25	0.81	0.85	0.66	2.87	3.07	2.89
	Monsoon	0.62	0.49	0.46	1.37	1.41	1.27	2.49	2.51	2.28
B1	Winter	0.81	0.85	0.66	1.74	1.78	1.67	2.12	2.14	2.08
	Summer	0.43	0.49	0.46	1.00	1.04	1.06	1.93	1.96	1.88
	Monsoon	0.46	0.67	0.62	1.06	1.04	1.00	1.27	1.41	1.37
B2	Winter	0.81	0.85	0.66	1.37	1.41	1.47	2.30	2.33	2.28
	Summer	0.62	0.67	0.66	1.00	1.04	0.86	1.56	1.59	1.47
	Monsoon	0.62	0.67	0.66	1.18	1.22	1.06	1.74	1.78	1.67

Table 6.4: Seasonal changes in mean, maximum and minimum temperatures from Hadley Centre GCM.

6.2.2 Demand Changes

The historic temperature series were 'morphed' using the Hadley projections, and applied to the demand sensitivity model. The detailed temperature and demand changes are presented as changes in daily demand profiles across key seasons and as monthly changes across the year.

Daily Demand Profiles

Figure 6.12 shows the mean projected changes for the four scenarios (A1, A2, B1 and B2) in winter (January). In each case the normalised demand is relative to the peak monthly demand in 2004. From the 2020s to the 2080s the range of increase in mean temperature rises for each time slice and scenario of between 0.62-1.00°C, 1.37-2.30°C and 2.12-4.55°C. The mean winter demand increases between 1.0-1.9% by 2020, 2.2-4.0% by 2050, and 3.6-7.3% by 2080.

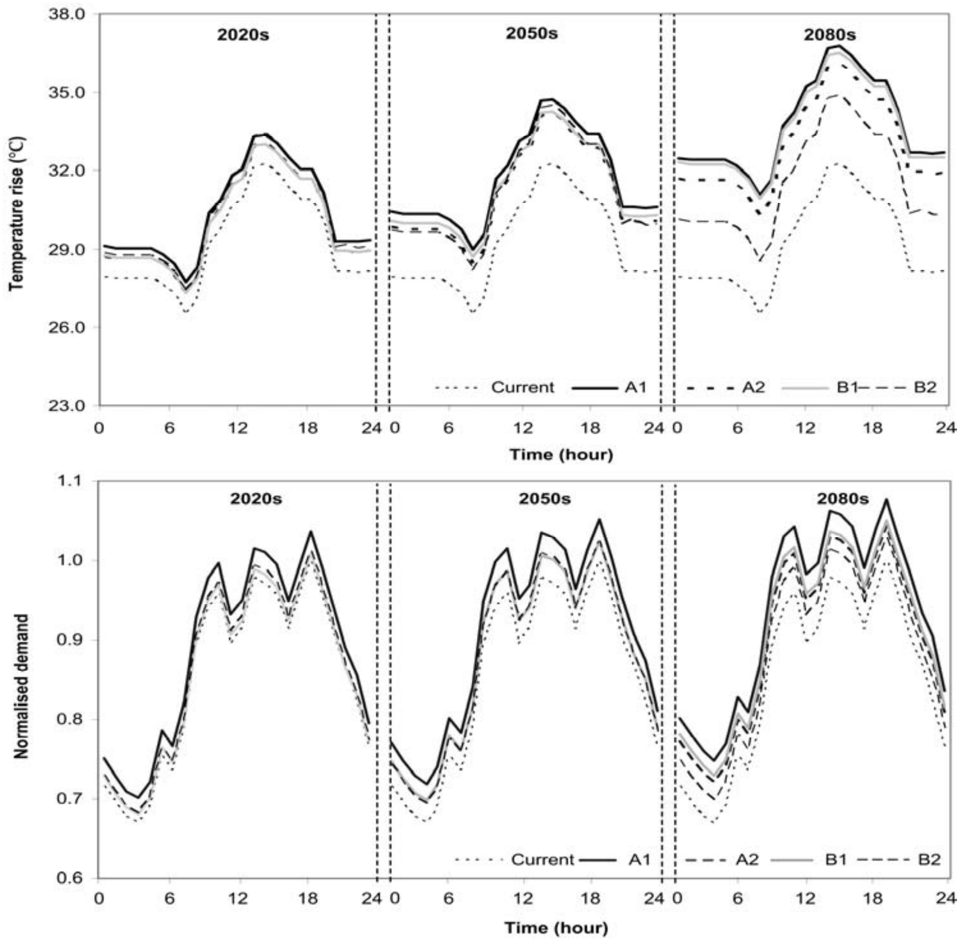

Figure 6.12: Average temperature and normalised changes to estimate the absolute changes in demand implied by climate change during winter for each time slice.

Figure 6.13 shows the mean projected changes for the four scenarios in the summer (April) season. Again the range of increases is greater further into the future with mean temperature rise ranging from 0.25-0.62°C, 0.81-1.93°C and 1.56-3.61°C in the 2020s, 2050s and 2080s, respectively. Summer mean demand increases by 0.9 to 2.1% in the 2020s, by 3.0% to 6.5% in the 2050s, and by 5.3- 12.1% in the 2080s.

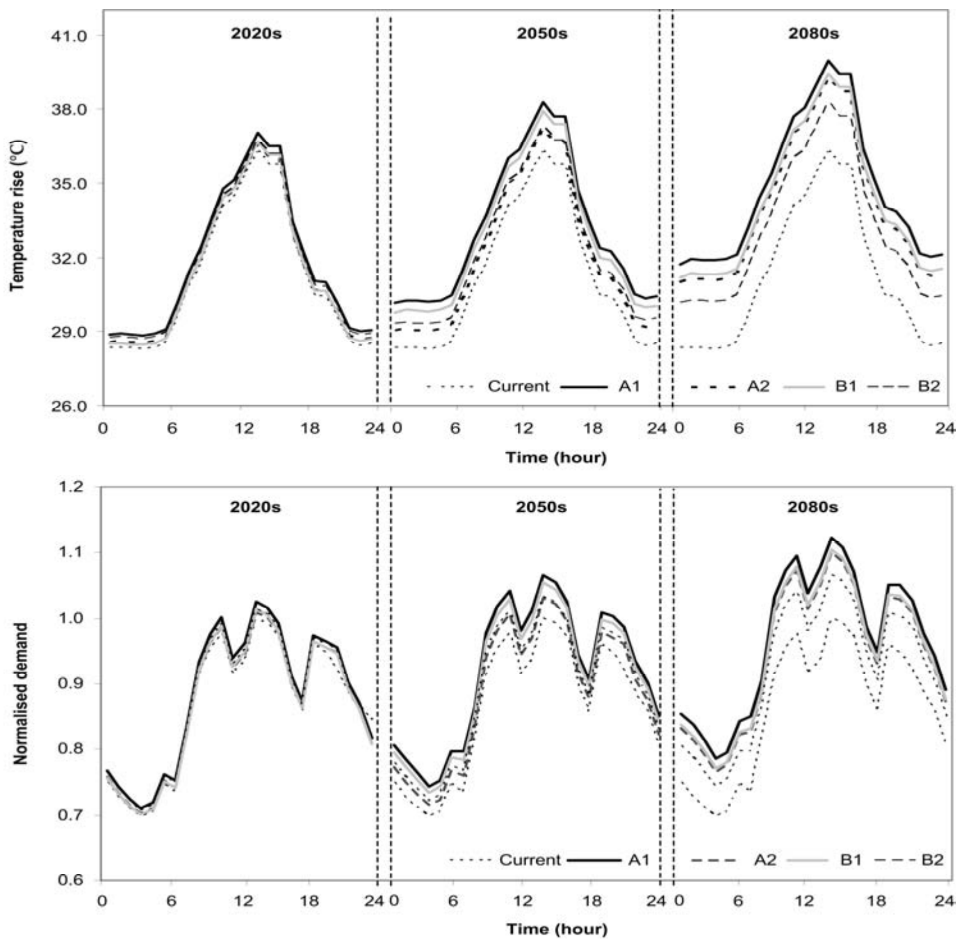

Figure 6.13: Average temperature and normalised changes to estimate the absolute changes in demand implied by climate change during summer for each time slice.

Figure 6.14 shows the mean projected changes for the monsoon (July) season. The range of increase in mean temperature across the scenarios covers 0.46-0.62°C in the 2020s, 1.06-1.56°C in the 2050s and 1.27-2.87°C in 2080s. The mean Monsoon demand increases between 1.1 and 1.5% in the 2020s, 2.6-3.8% in the 2050s, and 3.1-7.0% in the 2080s.

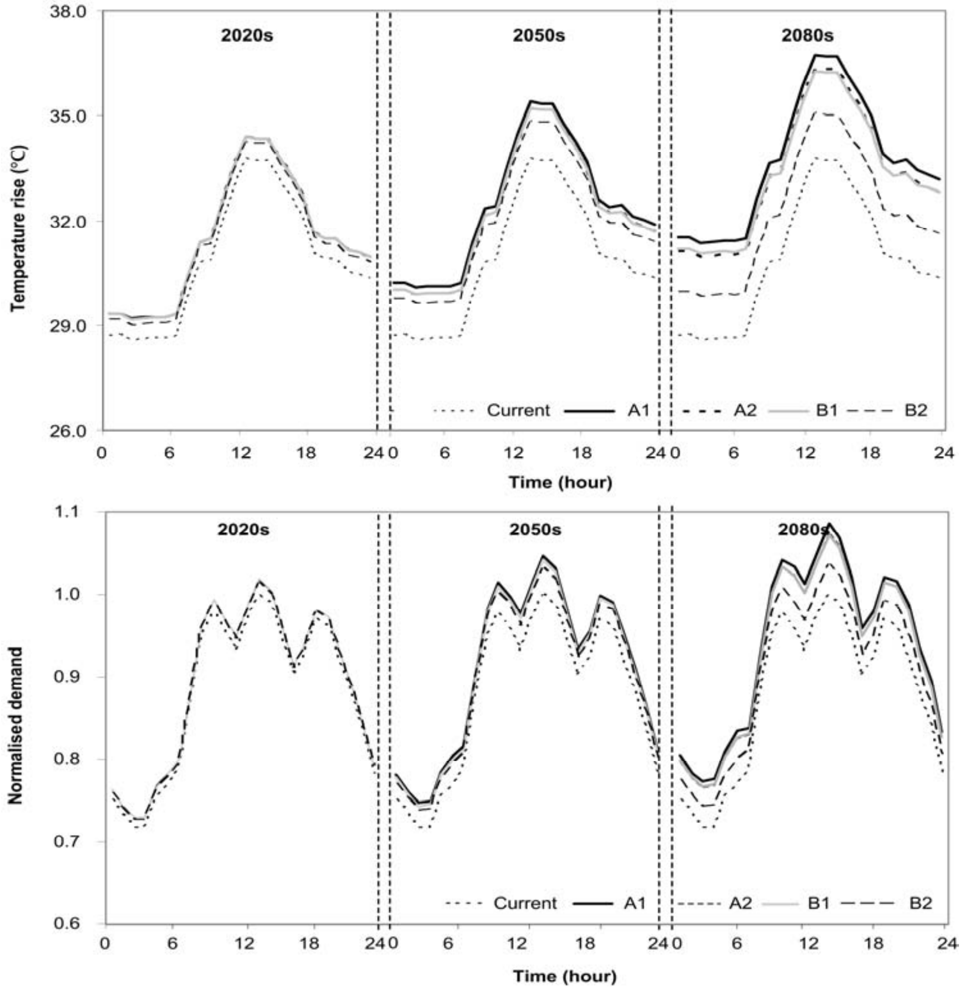

Figure 6.14: Average temperature and normalised changes to estimate the absolute changes in demand implied by climate change during monsoon for each time slice.

The resulting changes in seasonal peak and mean demand are summarised in Table 6.5. The highest changes are seen in summer for all four scenarios, as that is where the highest demand sensitivity coefficients occur and, importantly, peak demand rises more than mean demand. This gives very significant changes in summer peak demand of between 1.5 and 3.1% in the 2020s, 3.7 to 8.3% in the 2050s and 6.6 to 15.3% in the 2080s.

Year and Demand		Winter (%)				Summer (%)				Monsoon (%)			
		A1	A2	B1	B2	A1	A2	B1	B2	A1	A2	B1	B2
2020s	Peak	1.8	1.2	1.6	1.0	3.1	1.5	1.8	2.0	1.6	1.6	1.2	1.6
	Mean	1.9	1.3	1.5	1.0	2.1	0.9	1.6	2.1	1.5	1.5	1.1	1.5
2050s	Peak	3.7	2.9	3.2	2.0	8.3	4.0	4.2	3.7	4.7	3.7	2.8	3.6
	Mean	4.0	3.1	3.1	2.2	6.5	3.0	3.6	3.4	3.8	3.3	2.6	2.9
2080s	Peak	6.8	5.6	3.7	3.3	15.3	12.2	8.1	6.6	7.9	6.5	3.4	5.1
	Mean	7.3	6.2	3.6	4.0	12.1	9.6	6.6	5.3	7.0	6.1	3.1	4.2

Table 6.5: Change in seasonal peak and mean demand with temperature projections from the four scenarios on the Hadley Centre GCM.

Monthly Changes

The impact of the mean temperature changes in each monthly demand pattern across the 2020s, 2050s and 2080s was also examined for the four scenarios (A1, A2, B1 and B2). Figure 6.15 (a) and 6.16 (a) show the projected changes in monthly mean temperature in Thailand for the four scenarios for the 2020s, 2050s and 2080s. It can be seen that mean annual temperatures rise for A1, A2, B1 and B2 scenarios from 0.61 to 0.76°C in the 2020s, 1.20 to 1.94°C in the 2050s and 1.80 to 3.57°C in the 2080s. This is shown in table 6.6.

Scenario A1 and A2: Figure 6.15 (b) shows the resulting changes in maximum and minimum monthly demand change (%). The greater demand consumption in summer than winter and monsoon are the significant changes mean demand of 1.4 to 2.5% in the 2020s, 3.6 to 7.3% in the 2050s and 6.6 to 15.1% in the 2080s. The most significant annual peak demand increases due to the temperature rise of 2.5% in March (2020), 7.3% in March (2050) and 15.1% in March (2080) in scenario A1.

Monthly mean demand increases from between 1.3 to 2.3% in the 2020s, 3.0 to 5.0% in the 2050s and 5.5 to 11.0% in the 2080s. Peak demand also increases due to the rise in temperature: the increases in peak demand are 2.3% (in March 2020), 5.0% (in March 2050) and 11.0% (in March 2080) in scenario A2.

Year and °C	(°C) increase mean annual temperature rise			
	A1	A2	B1	B2
2020s	0.76	0.67	0.61	0.62
2050s	1.94	1.54	1.20	1.20
2080s	3.57	2.96	1.80	1.95

Table 6.6: Projected increase mean annual temperature rise for 2020s, 2050s and 2080s with the Hadley GCM scenario A1, A2, B1 and B2.

Scenario B1 and B2: Figure 6.16 (b) shows the resulting changes in maximum and minimum monthly demand change (%). Monthly mean demand increases from between 1.0 to 2.0% in the 2020s, 2.9 to 4.5% in the 2050s and 3.1 to 7.3% in the 2080s. Peak demand also increases due to the rise in temperature: the changes in peak demand are 2% (in February 2020), 4.5% (in March 2050) and 7.3% (in March 2080) in scenario B1.

B2 scenario: the monthly mean demand increases from between 1.0 to 3.2% in the 2020s, 2.2 to 4.6% in the 2050s and 3.7to 8.4% in the 2080s. Peak demand increases and occurs due to the temperature rise give most significant changes in percentage of this scenario between 3.2% (in March 2020), 4.6% (in March 2050) and 8.4% (in March 2080).

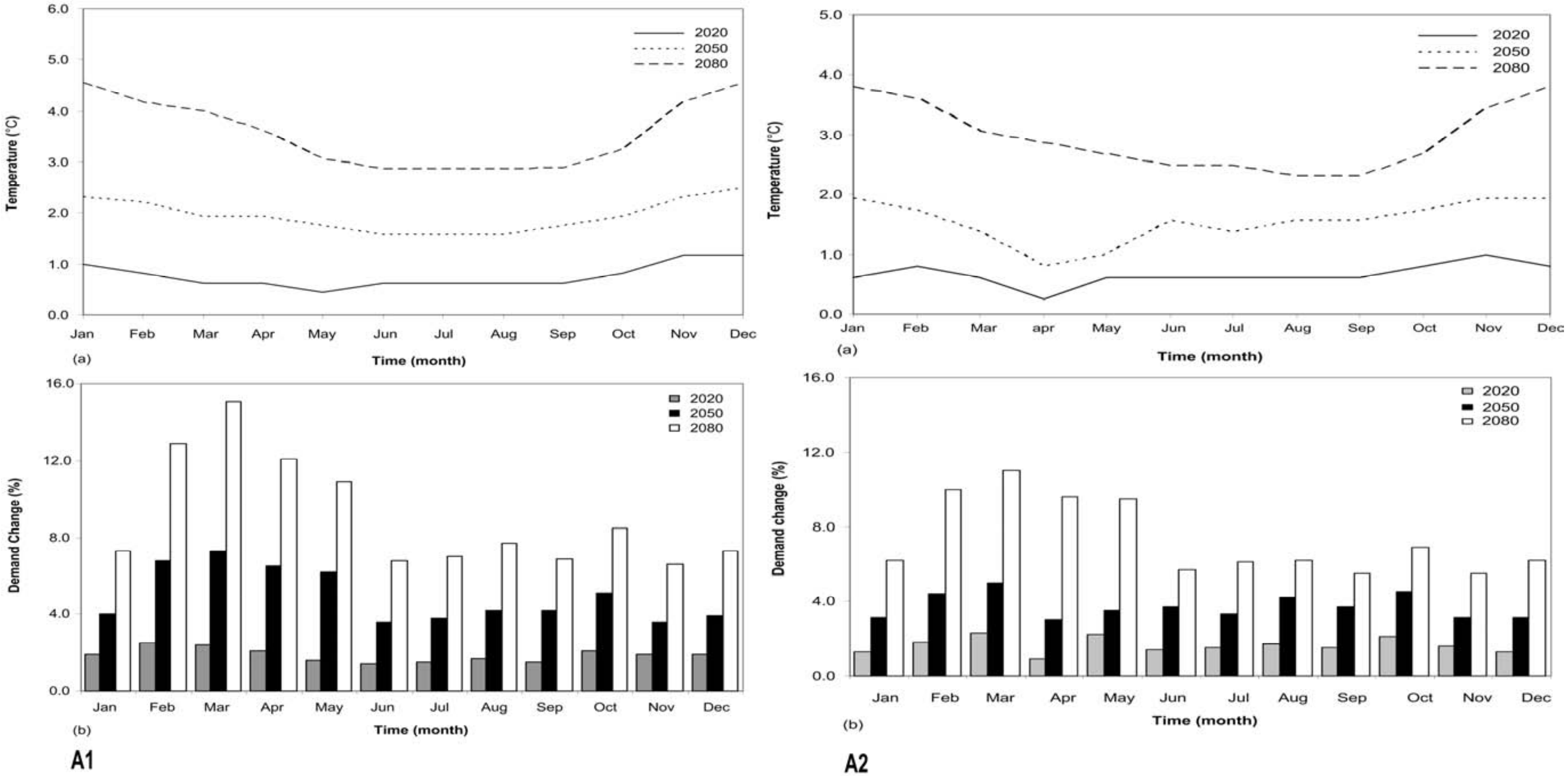

Figure 6.15: Mean monthly changes in (top) temperature and (bottom) demand change for 2020, 2050 and 2080 with the Hadley GCM scenario A1 (left) and A2 (right).

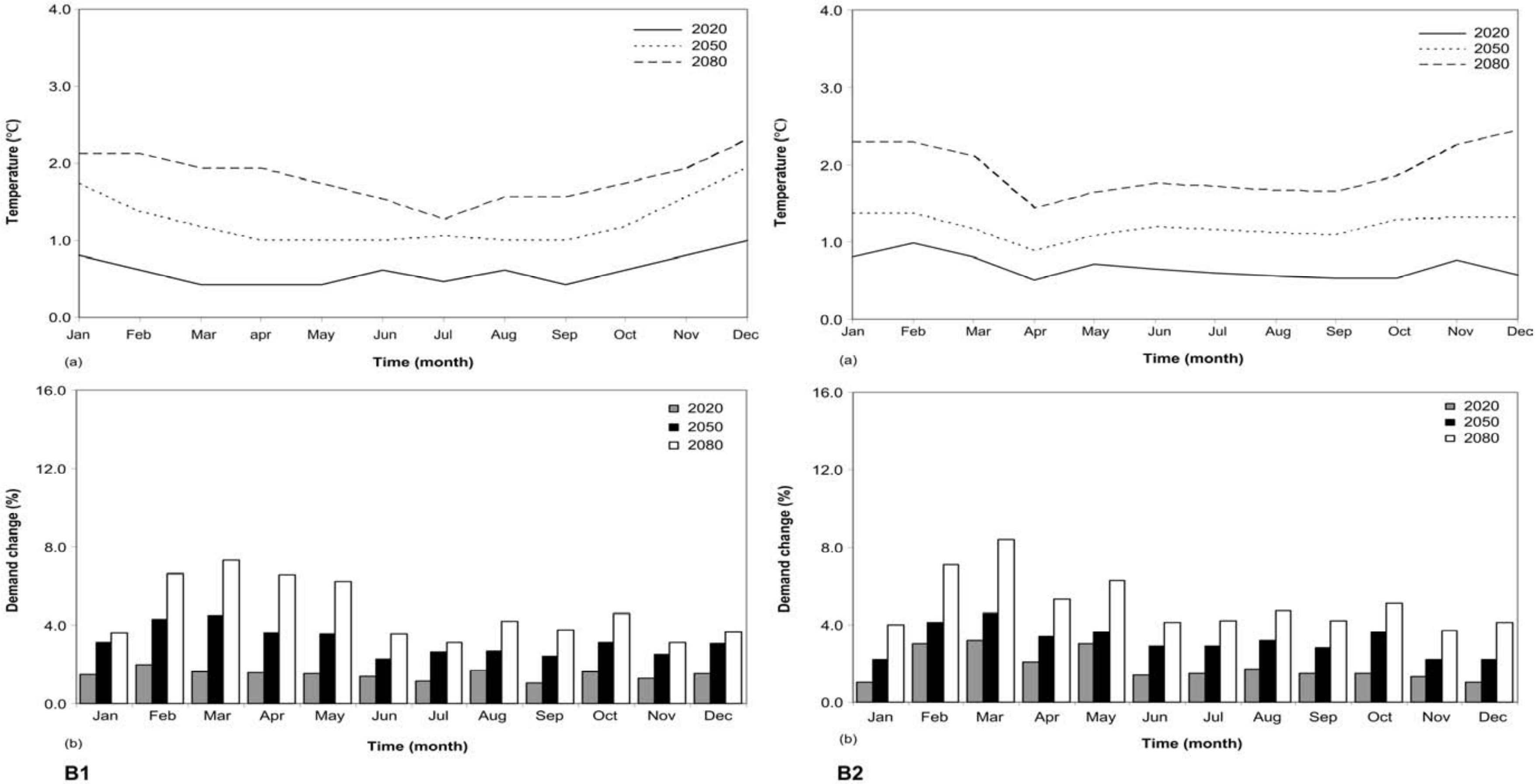

Figure 6.16: Mean monthly changes in (top) temperature and (bottom) demand change for 2020, 2050 and 2080 with the Hadley GCM scenario B1 (left) and B2 (right).

6.2.3 Absolute Demand Changes

Absolute changes in peak demand were calculated by taking the demand of each year projected by the long-term model (i.e. SRES growth rates) and multiplying it by the percentage change in peak demand for the summer.

$$\Delta\ \text{(Absolute Demand)} = \text{Peak Demand} \times \Delta\ \text{(Peak Demand)} \qquad (6.5)$$

Table 6.7 shows the resulting future absolute demand changes for each scenario. There are fairly similar increases in peak demand across the four scenarios projected for the 2020s of 600 to 1400 MW. However, the spread in demand covers 12 GW by the 2050s and 55 GW by the 2080s. The larger spread comes from the combination of the large spread in baseline demand levels and the larger spread in percentage demand changes created by diverging temperature projections.

Model	GW increase per peak sensitivity model			
	A1	A2	B1	B2
2020	1.4GW	0.6GW	0.8GW	0.7GW
2050	14.8GW	5.8GW	4.9GW	4.1GW
2080	64.0GW	29.5GW	8.0GW	9.1GW

Table 6.7: Projected change in absolute demand for each scenario.

6.3 Influence of Socio-Economic Model Choice

The assessment so far has examined the potential changes in demand as projected by the Hadley GCM and the AIM socio-economic model. There were significant variations in demand and consequently demand changes projected with each of the scenarios (A1, A2, B1 and B2) modelled by AIM. As highlighted in Chapter 2 and earlier in this chapter, the full range of SRES scenarios runs to over 40 separate analyses and there are several GCM runs based on these. This section aims to look a little closer at the choice of socio-economic model and the influence it has on the projected long-term demand and absolute temperature changes.

To do this it compares the outputs and the consequent impact on demand for the four scenarios as modelled by four separate SRES modeling groups. These were the:

1. AIM from Japan (used earlier);
2. Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) from the International Institute of Applied Systems Analysis (IIASA) in Austria;
3. Mini Climate Assessment Model (MiniCAM) from the Pacific Northwest National Laboratory (PNNL) in the USA and;
4. ASF from ICF International, a global professional service firm.

The same process of extracting 10-yearly electricity growth rates and applying these to the 2004 Thai peak demand was followed for each of the scenarios. Table 6.8 shows the range of future peak demand projected by the four socio-economic models for the four scenarios (A1, A2, B1 and B2) in the 2020s, 2050s and 2080s. Overall the range covers 34 to 49GW in the 2020s, 78 to 221GW in the 2050s and 137 to 418GW in the 2080s. Comparison with the regression models estimates for demand is shown in Appendix B.

Year and Demand	Range of peak demand (GW)			
	A1	A2	B1	B2
2020s	43 to 49	37 to 41	38 to 40	34 to 41
2050s	178 to 221	97 to 146	94 to 125	78 to 112
2080s	320 to 418	208 to 242	118 to 151	137 to 216

Table 6.8: Projected range of peak demand across the models for each scenario.

Figure 6.17 shows the projections of future demand from 2010 to 2100 for the A1 and A2 scenarios and Figure 6.18 shows the same for the B1 and B2 scenarios. All demonstrate the progressive divergence of model projections (highlighted in Table 6.7), from relatively low levels in the 2020s to much more significant amounts in the 2080s, particularly for the A1 scenario. In all cases, the scenarios giving the highest and lowest growth rates in demand are not consistently the same. For example, the A1 AIM projection shows the lowest demand in 2050 but the highest in 2080. This underlines the differences between modeling approaches and assumptions.

Applying the percentage changes in demand indicated by the Hadley Centre temperature changes across the range of each of the demand projections gives the figures shown in Table 6.9. The spread of changes reflects the size of the spread in baseline demand, with larger ranges occurring in later periods and in the A1 and A2 scenarios.

Year and Demand	Absolute changes in peak demand (GW)			
	A1	A2	B1	B2
2020s	1.3 to 1.4	0.5 to 0.6	0.7 to 0.8	0.7 to 0.8
2050s	14.8 to 18.1	3.9 to 5.8	4.0 to 5.1	2.8 to 4.1
2080s	50 to 64	25.3 to 29.5	8.0 to 12.0	9.1 to 14.0

Table 6.9: Range of projected changes in peak demand across the models for each scenario under the Hadley Centre temperature projections.

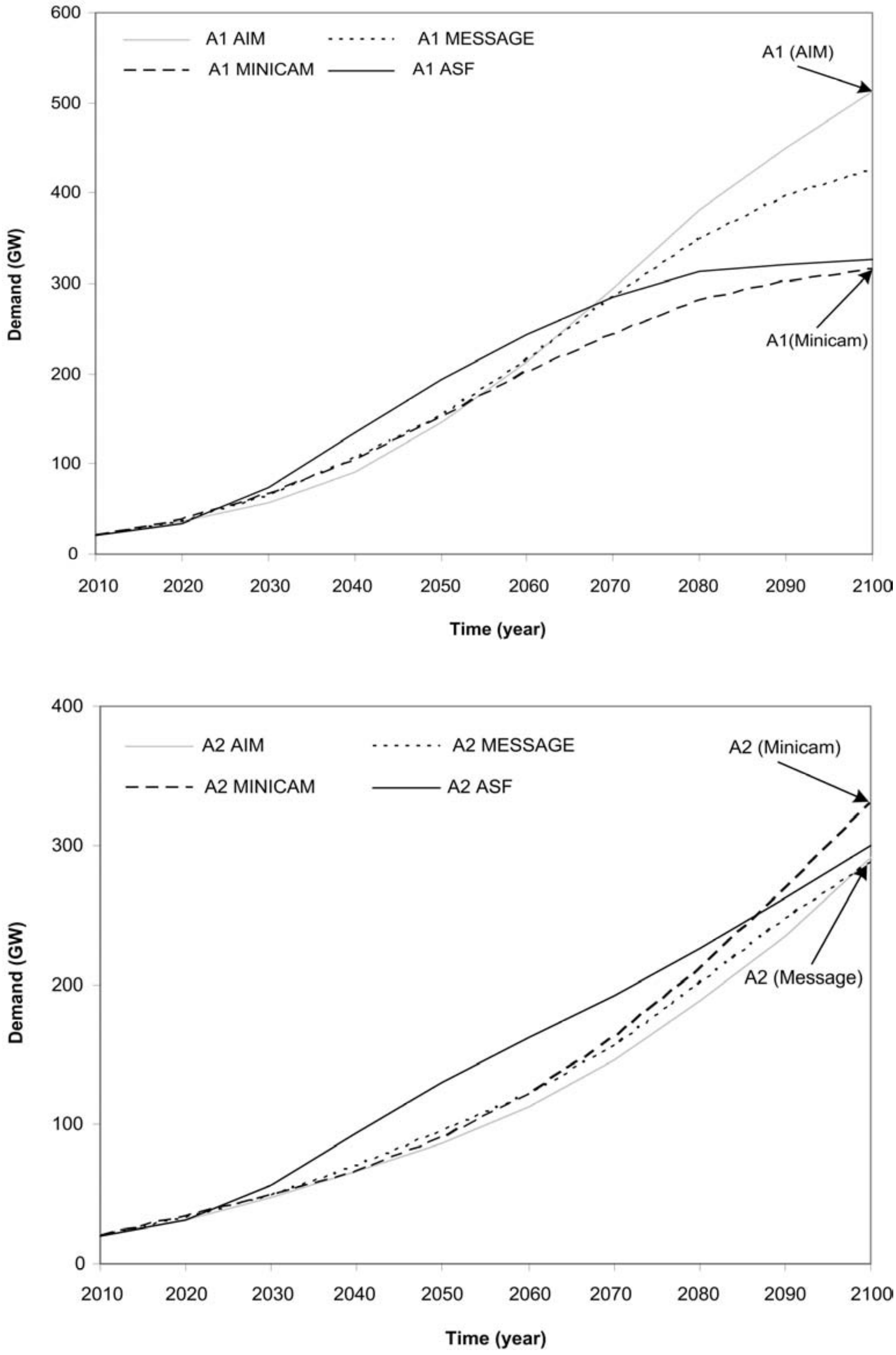

Figure 6.17: Projected demand to 2100 for A1 (top) and A2 (bottom) scenarios for four SRES models.

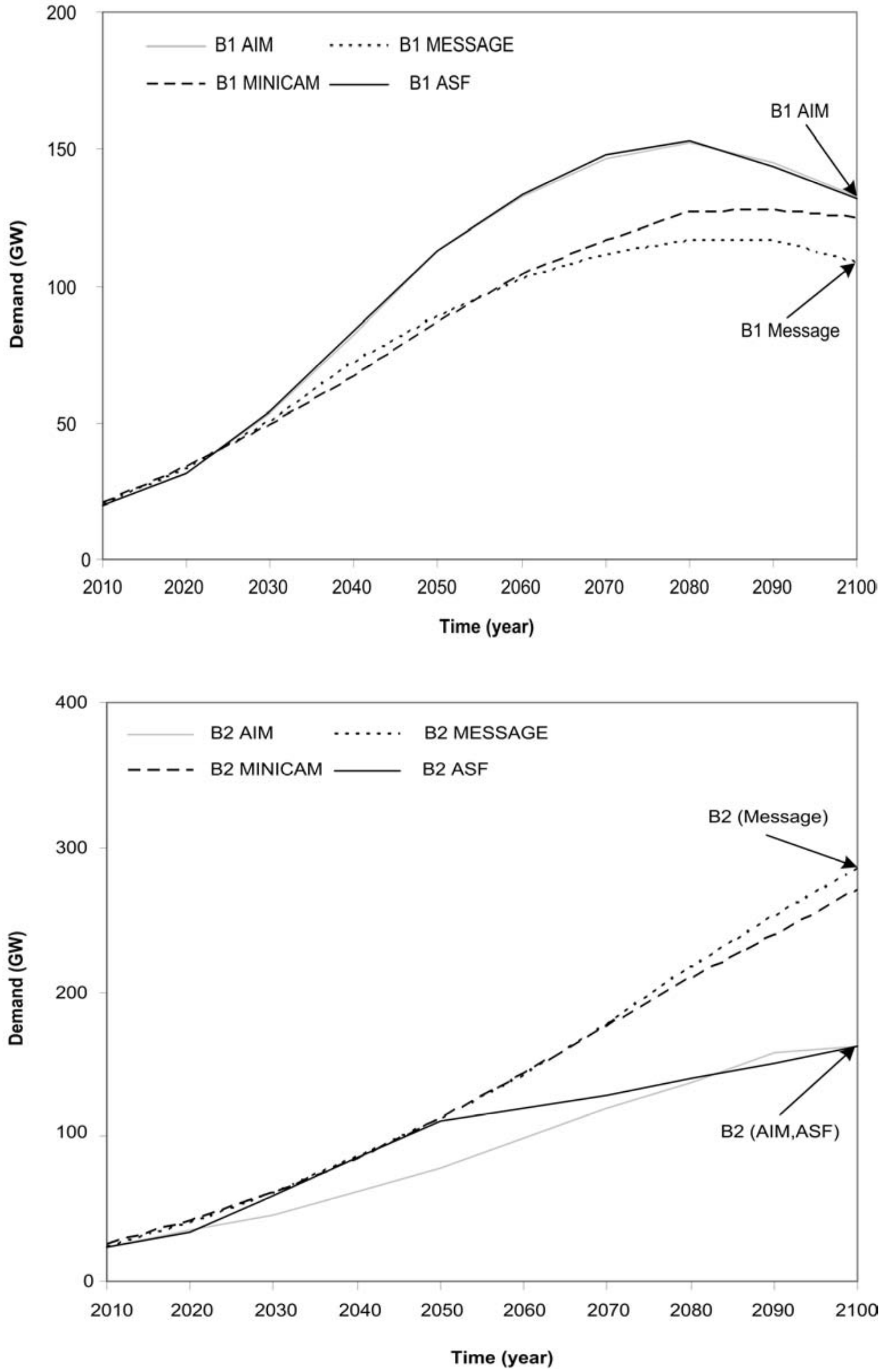

Figure 6.18: Projected demand to 2100 for B1 (top) and B2 (bottom) scenarios for four SRES models.

The comparisons with the other three SRES socio-economic models serve a useful purpose in testing whether the results presented with the AIM model are representative of the SRES scenario set as a whole. With the Hadley Centre the only climate model applied the relative changes in demand in each time period for each scenario will be the same. The different demand levels suggested by the socio-economic models suggest that the absolute (MW) changes will differ despite the use of the same temperature projections and relative changes in demand. Figure 6.19 shows the extreme range of demand projections for all of the socio-economic models applied including with the projections from the AIM model. What is apparent is that the spread of capacities suggested by the demand models is greater than the absolute demand changes suggested in Table 6.8.

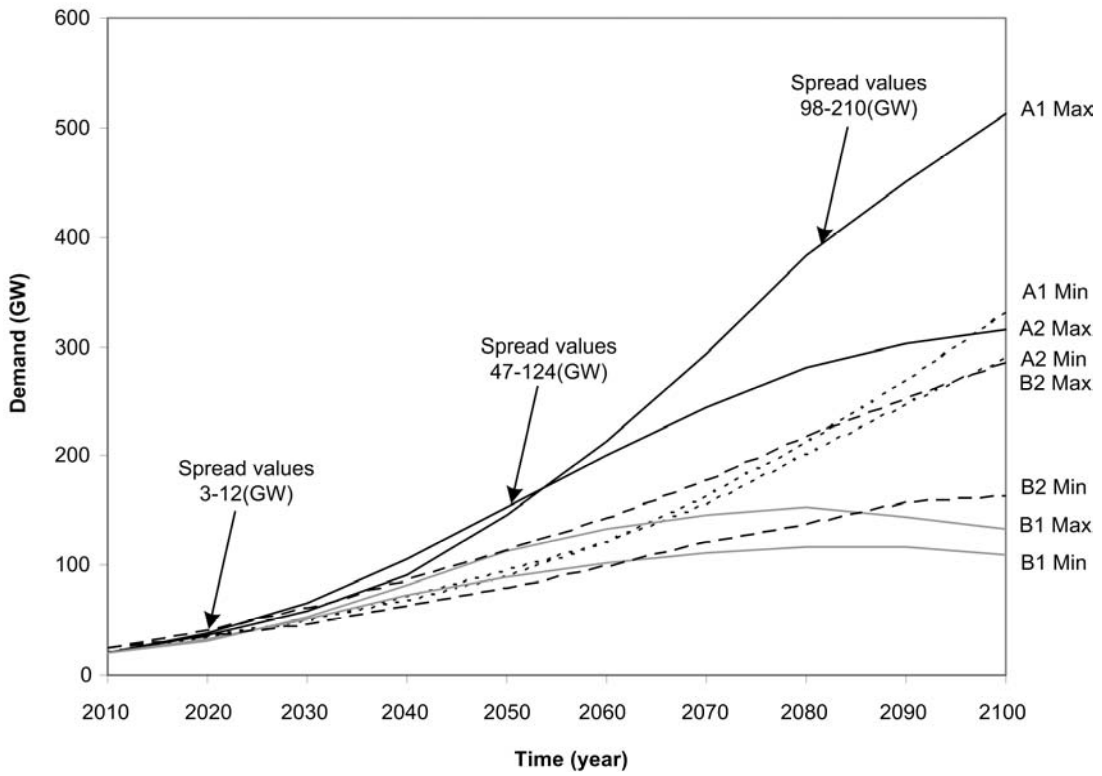

Figure 6.19: The minimum and maximum projected demand from the four socio-economic models for the four scenarios over 2010 to 2100.

6.4 Chapter Summary

This chapter used the simple weather sensitivity model to project realistic changes in Thailand's electricity demand. It achieved this by combining the temperature projections of the Hadley Centre GCM and the socio-economic projections of the AIM model. The changes were significant, particularly by the 2050s and 2080s, and showed large increases in demand across the year with particularly significant increases in summer peak demand. The influence of the choice of socio-economic model was examined by repeating the absolute demand projections with three other SRES models.

Chapter 7

Discussion and Conclusions

This final chapter includes a summary and discussion of the main results of the research and work done, conclusions of this thesis and a discussion of future work. There are issues involved with the role of climate change and realistic changes in future demand. Conclusions are drawn from this work, with reference to the research objectives and scope of this thesis outlined in Chapter 1.

7.1 Thesis Summary

Figure 7.1 shows the research progress in this thesis. It began with a literature review of the climate change issue (Chapter 2), then Chapter 3 which presented the effects of climate change on the electricity industry. Chapter 4 discussed the structure of the Thai electricity industry and the differing patterns of electricity use. In Chapter 5, the effect of weather conditions on electricity demand patterns was investigated: several different modelling approaches were discussed and a linear regression method was chosen to model the demand sensitivity to cooling degree hours (a proxy for temperature). Finally, in Chapter 6 the temperature projections from the UK Hadley Centre climate model were combined with socio-economic scenarios for the IPCC SRES to investigate how changing climate will affect Thailand's electricity demand in the future. A summary of each chapter follows.

Chapter 2 presented the summary of the international scientific consensus of climate change based on greenhouse gas emissions. Future climate change could threaten human activity in two ways: directly and indirectly. The emission of greenhouse gases is increasing as the standard of living rises and more fossil fuels are burned. These increases will enhance the greenhouse effect and cause a significant change in temperature and changes in other climate variables (wind speed, humidity, precipitation, evaporation, runoff, and cloud cover).

In Chapter 3 the impact of climate change on the electricity industry is assessed. In the long term, climate change could affect the planning and financing of future investments in electricity generation and transmission. However, a key result of climate change is that large changes in temperature over the long term which could lead to a shortfall between generation and consumption. Problems resulting from climate change could influence generation through sea level rise threatening coastal power stations and high temperatures could affect transmission line ratings through extreme sagging of lines.

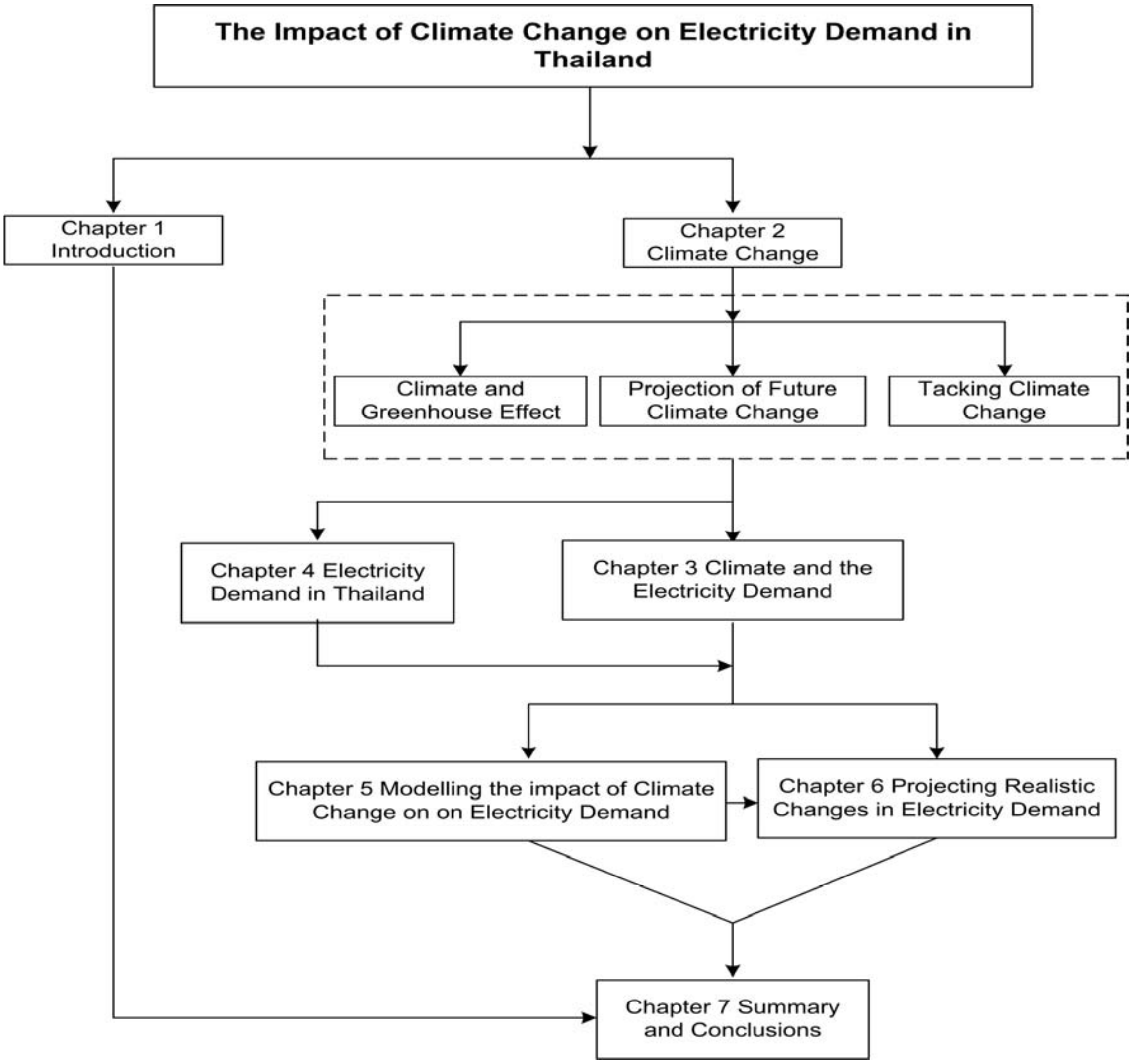

Figure 7.1: Flow chart showing the research progress in this thesis.

Chapter 4 introduced the structure of the electricity industry in Thailand and highlighted the major growth in demand over recent decades which is expected to continue into the future as living standards and population increase. Electricity consumption is analysed by customer sectors and on a daily and seasonal basis.

In Chapter 5, the objective was to examine the impacts of weather and type of day (e.g. weekday, weekend and holiday) on electricity demand. The first part of the chapter examined the alternative approaches to modelling demand before presenting a simple linear regression model that divided demand into hourly time-slices for each month across the year and identified the influence of temperature through the use of the cooling degree hours measure. The regression method (also known as the weather sensitivity model) was found to model the daily electricity consumption patterns well. The variation in sensitivity to temperature across the day and between months was highlighted by applying uniform temperature changes (of 1 and 2°C) across the year.

Chapter 6 defined a way of providing credible forecasts of future Thai electricity demand based on coherent GDP, population and temperature projections. These were based on four representative socio-economic scenarios developed for the IPCC Special Report on Emissions Scenarios which provide consistent projections of increases in population, GDP greenhouse gas emissions and electricity demand. The corresponding temperature changes projected from the Hadley Centre GCM were applied to the weather sensitivity model to estimate changes in daily demand profiles across the year. The resulting demand changes were significant, particularly for summer months across all time-scales considered.

7.2 Discussion of Results

7.2.1 Implications of Results

Thailand's CO_2 emissions in 1998 were around 192 Mt CO_2 with emissions from solid fuels of 39.7 Mt CO_2, liquid fuels of 109.2 Mt CO_2, gas fuels of 28.6 Mt CO_2 and cement manufacturing of 15 MT CO_2 (UNFCCC (United Nations Framework Convention on Climate Change, 2002). Although Thailand's gas-fired power plants supply 70% of the total electricity the sector has considered reducing emissions of sulphur dioxide (SO_2) and nitrogen oxides (NO_2) by replacing coal fired plants with gas plants. It is reasonable to assume that in the short-term at least that any increase in demand will be met by gas plant.

Higher temperatures due to climate change was shown (Chapter 6) to raise peak summer demand by up to 15% by the 2080s relative to a non-climate change projection. The AIM socio-economic scenarios and the Hadley Centre GCM projections suggested peak capacity requirements increased by 0.7-1.4GW in the 2020s, by 4.1 to 14.8GW in the 2050s and by 9.1 to 63.9GW in the 2080s. Assuming increased demand is met by new CCGT stations costing $695/kW (Sarkar S.K., 2006) and no real change in costs, this implies additional capital expenditure of between $0.48 and $0.97 billion by the 2020s, $2.8 to 10.2 billion by 2050s and $6.3 to 44.4 billion by the 2080s. This sort of increase is of a similar magnitude to the $200 to 300 billion suggested by Linder *et al.* (1987) for the US by 2055.

The corresponding increase in annual electricity demand for the AIM and Hadley Centre scenarios was found to be lower than changes in peak. However, the changes are still large: mean demand rises 2 to 2.1% in the 2020s, equivalent to an extra 596 to 763 MW on average (5.2-6.7 TWh/year)); the 3.5 to 5.3% change for the 2050s adds an extra 7.4 to 3.1 GW of demand (26.8-64.5 TWh/year) while the 2080s sees an extra 5.6 to 9.8% in mean demand representing 6.1 to 31.9 GW (or 53-280 TWh/year). Again assuming extra demand is met by CCGT stations this implies significant extra gas use and operational costs. Assuming current gas prices apply across all time periods (2.76 US cents/kWh), that natural gas has a calorific value of 55MJ/kg and the CCGT station is 60% efficient the following increases are implied by the AIM scenarios.

The increase in gas use in the 2020s ranges from 0.6 to 0.7 Mt/year which, in real terms, equates to $240 to 307 million per year of additional expenditure. For the 2050s the gas use is raised by 2.9 to 7.0 Mt/year costing an extra $1.2 to 3 billion/year while the very large increases in energy use and by the 2080s suggest that climate change could result in the use of an additional 5.8 to 30.5 Mt/year of gas worth $2.4 to 12.9 billion/year.

In addition to the large costs of the extra gas, there is additional environmental damage as increased gas burning will raise CO_2 emissions significantly. With the mass of CO_2 2.75 (44/16) times that of methane (natural gas) the additional annual CO_2 emissions caused by the climate-led increase in demand is 1.6 to 2.0 Mt CO_2 in the 2020s, 8.0 to 19.3 Mt CO_2 in the 2050s rising to an extra 15.9 to 83.9 Mt CO_2 in the 2080s. The environmental consequences of meeting the extra demand implied by climate-led increases in temperature by building coal-fired power stations are far greater.

7.2.2 Reliability of Results

Although the study has followed IPCC best practice in using multiple socio-economic scenarios to explore the range of future demand, there is clearly a lot of uncertainty attached to the projections. This is caused by several factors:

- The socio-economic scenarios used
- The GCM projections
- The demand model

The range of demand outcomes across the four AIM scenarios applied here is large although the analysis in Section 6.3 with three other EEE models showed the range was representative of the larger set of possibilities. Absolute confidence in this could however, only be achieved by assessing all 40 SRES scenarios which is clearly beyond this work.

Perhaps the largest uncertainty that remains relates to the use of the temperature projections from a single GCM. The use of other GCMs in addition to the Hadley Centre model would increase the spread of the results and provide a more complete assessment of the uncertainty. Further work is required in this area.

A regression model was used because of the preliminary nature of this work and because of the limitations on available data and the concentration of demand in the Bangkok area. The reliability of regression models is somewhat limited, as they are based on only a single year of data and a single variable. Although the relationships were similar to recent years they do not capture the full range of climate or demand conditions and no account has been made of the effect of changing rates in ownership of temperature-sensitivity appliances like air-conditioning.

The demand projections assume that the load factor and demand patterns remain the same far into the future: they do not account for the effect of energy efficiency or micro-generation employed to mitigate climate change which will significantly change demand profiles but will also affect the sensitivity of demand to rising temperature.

Finally, it is important to emphasise that the demand changes suggested here are only indications and should *not* be interpreted as being forecasts for specific calendar years. The absolute changes in demand illustrate the *scale* of possible changes rather than a forecast of the exact amount of extra generation or transmission capacity required.

7.2.3 Recommendations for Future Work

There are a range of possible ways of refining and extending the approach taken in this work. A more "bottom up" approach could be used. For example, models might take into account the variety of building types in Thailand when modelling the response to changing outdoor temperature. This would to allow study of building response to climate and the effect of measures designed to mitigate climate change (e.g., solar PV, etc.). This would require more detailed assessment of other weather variables. The use of additional GCM scenarios would be beneficial in understanding the uncertainty in temperature projections. Further work is required to allow such projections to be used in practice by electricity planners in Thailand. The use of long term plant investment models would also provide a more detailed assessment of the implications for additional generation, transmission and distribution investment. Finally, other developing nations require assessment.

7.3 Conclusions

There is a scientific consensus that human activity is leading to global warming. The emission of greenhouse gases has accelerated from the Industrial Revolution, primarily from the burning of fossil fuels in electricity generation and transportation. Rapid economic growth in developing countries will increase emission levels by the end of this century.

Climate change in the future may cause increased temperature of 1.4-5.8°C by the end of this century. The effect of changing climatic patterns would cause changes in regional precipitation patterns and other meteorological variables. The impact of these changes may affect human living standards. Climate change will also affect the electricity industry and specifically changes in temperature will alter space heating and cooling requirements and affect electricity demand.

To assess the influence of climate change on Thailand's future electricity demand a regression model was developed to capture daily demand sensitivity to temperature. Thai demand was found to be sensitive to temperature change specifically in summer. A series of representative socio-economic scenarios from the IPCC Special Report on Emission Scenarios together with changes in mean temperature and diurnal temperature range projected by the Hadley Centre climate model were used to estimate realistic changes in Thai demand in the three future periods: the 2020s, the 2050s and the 2080s. With mean annual temperatures in Thailand projected to rise by 1.74 to 3.43°C by 2080, peak demand was estimated to increase by an additional 1.5 and 3.1% by 2020, 3.7 to 8.3% by 2050 and 6.6 to 15.3% by 2080, representing many gigawatts of additional demand.

Although the implications for annual energy consumption are less severe than for peak demand, the economic consequences of the additional demand are significant with many billions of dollars required to construct and operate additional generation. If fossil-fuelled generation is constructed to meet the shortfall, millions of tonnes of additional CO_2 emissions may result.

It is apparent that the Thai utility needs to incorporate climate change effects within its load forecasting and system planning regime.

The research set out to examine the hypothesis that "weather variability and climate change will significantly affect the electricity demand patterns and growth in Thailand". On the basis of the work presented and the results from the case study this hypothesis appears to be correct.

Chapter 1

Introduction

1.1 Thesis Background

Climate change or global warming is the greatest scientific and political challenge of the twenty-first century. Climate change is a serious threat to society and is regarded by the United Kingdom's Chief Scientist as a "greater threat than terrorism" (BBC News, 2004). Climate change is the expected result of burning of fossil fuels, particularly for power generation, and deforestation which have altered the levels of greenhouse gases in the atmosphere. With the increasing industrialisation of developing countries such as Thailand, increased emissions of greenhouse gases are expected over the century.

Emissions of greenhouse gases are regarded by a majority of scientists as being responsible for the significant increases in global surface temperatures over the past centuries and are likely to lead to increases in the future (IPCC, 2001). The Third Assessment Report from the Intergovernmental Panel on Climate Change (IPCC) suggested a rise of between 1.4 and 5.8°C in global average temperatures by 2100 (IPCC, 2001). The 2007 Fourth Assessment Report updates these figures and states best estimates of between 1.8 and 4.0°C within a likely range of up to 6.4°C (IPCC, 2007). Figure 1 shows the past and range of projected future global average surface temperature rises and clearly shows that yearly temperature change has accelerated. Considerable research has been done on the effects of changes in temperature and other climatic variables. These studies suggest the rising temperatures will have detrimental impacts due to rising sea levels, increased storm activity and damage and changes in the availability of water.

The power sector is a major contributor to greenhouse gas emissions and climate change. Additionally, the electricity sector in many countries will be affected by a changing climate. With many components of electricity demand already sensitive to temperature and other climate variables, rising temperatures will affect the energy used for air-conditioning, space heating and water pumping. Changes in peak loading are particularly important, since on occasions of extreme temperatures this is likely to stress electricity systems in meeting demand. With many nations investing very large sums of money in building and renewing electricity systems there is a need to understand the influence of climate change and plan for its effects. This is particularly the case for developing nations such as Thailand.

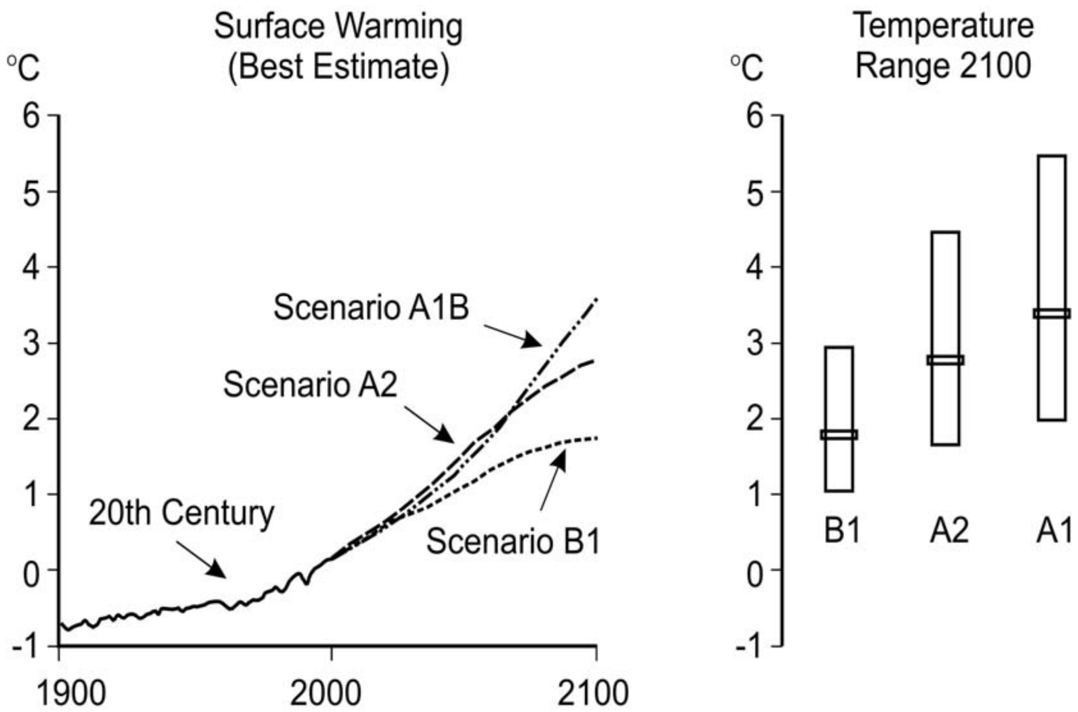

Figure 1: Left: The past and range of projected future global average surface temperature rise; Right: Range for temperature scenarios, after (Houghton, 2005).

1.2 Research Objective and Scope

The project had several different objectives:

- To gain an understanding of the scientific basis for climate change and the long term changes in climate that may occur.

- To examine how global climate change can affect the electricity sector through its impact on power generation, transmission and distribution, and electricity demand.
- To examine existing research on climate impacts on electricity demand, to identify limitations and research needs.
- To develop a method to examine the potential impacts on demand based on credible long term trends in climate and electricity demand, and to apply it to Thailand as a case study.
- To consider the implications for electricity industry in Thailand.

1.3 Thesis Statement and Contribution to Knowledge

The project will test the hypothesis that:

> "Weather variability and climate change will significantly affect the electricity demand patterns and growth in Thailand"

The potential for climate to influence demand is well known among researchers and increasingly the electricity utilities in the developed world. However, there is limited knowledge of impacts and little analysis carried out for developing nations like Thailand.

This research is likely to be of interest to climate impact researchers and more importantly to policymakers and electricity planners in Thailand who will have to consider, plan and manage the consequences of climate change.

1.4 Thesis Outline

The results from this research are presented in the following seven chapters with appendices.

Chapter two is a general introduction to climate change and specifically the role of emissions of greenhouse gases in global temperature change.

Chapter three examines the role of weather and climate uncertainty in the electricity industry and examines the literature on climate impacts on generation, transmission and distribution, and electricity demand.

Chapter four sets out the first part of the case study of Thailand by giving a background to the Thai electricity sector and the specific nature and features of demand.

Chapter five begins with a brief assessment of options and approaches for modelling the effect of climate change on electricity demand in Thailand. Based on the available information and the features of the Thai system it presents and validates a modelling approach developed to analyse the sensitivity of demand patterns to changing climate.

Chapter six uses the procedure developed in Chapter five to analyse realistic changes in Thailand's daily, monthly and long-term demand based on credible socio-economic projections and the output of a range of scenarios from climate models.

Chapter seven summarises the results from the research and discusses its limitations and implications. The contribution to knowledge is highlighted and future work is detailed.

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Appendix A

Data Sources of Weather Sensitivity Assessment Models

A.1 Detailed a Temperature-Demand Relationship

Figure A.1 to A.4 shows the relative sensitivity of CDH patterns in the normal demand consumption patterns, the longer holiday and the major impact of weather variable uncertainty which will be affected by the changes in demand patterns in Thailand.

Figures A.5 to A.6 show the variation in the β_1 coefficient for each hour throughout the weekend days and holiday days. These two diagrams show β_1 intercept curves for a weekend and holiday with three seasons. The cooling degree is less significant in weekend electricity demand. This is most likely due to the difference between the weekday and the weekend in work and lifestyle patterns. The public holiday curve shows a greater similarity with the weekends compared to the weekday curves.

Figures A.7 to A.9. show the sensitivity of individual hourly demand (β_{CDH}) for each month over the year as well as comparisons between actual and modelled daily demand profiles. The overall sensitivity is higher in summer than in other seasons. These are reflected in the performance statistics given in Tables A.1 to A.3. Tables A.1 to A.3 show the detailed data for CHD sensitivity of demand (β_{CDH}) and measures of performance of the regressions for each of the time-slices in each month. The models indicate a reasonable fit with the actual demand with mean absolute percentage errors (MAPE) as shown in the table. These are backed up by high coefficients of determination (R^2) of in most hours. R^2 explains the proportion of the variance in demand that can be explained by the variance of CDH in that time-slice.

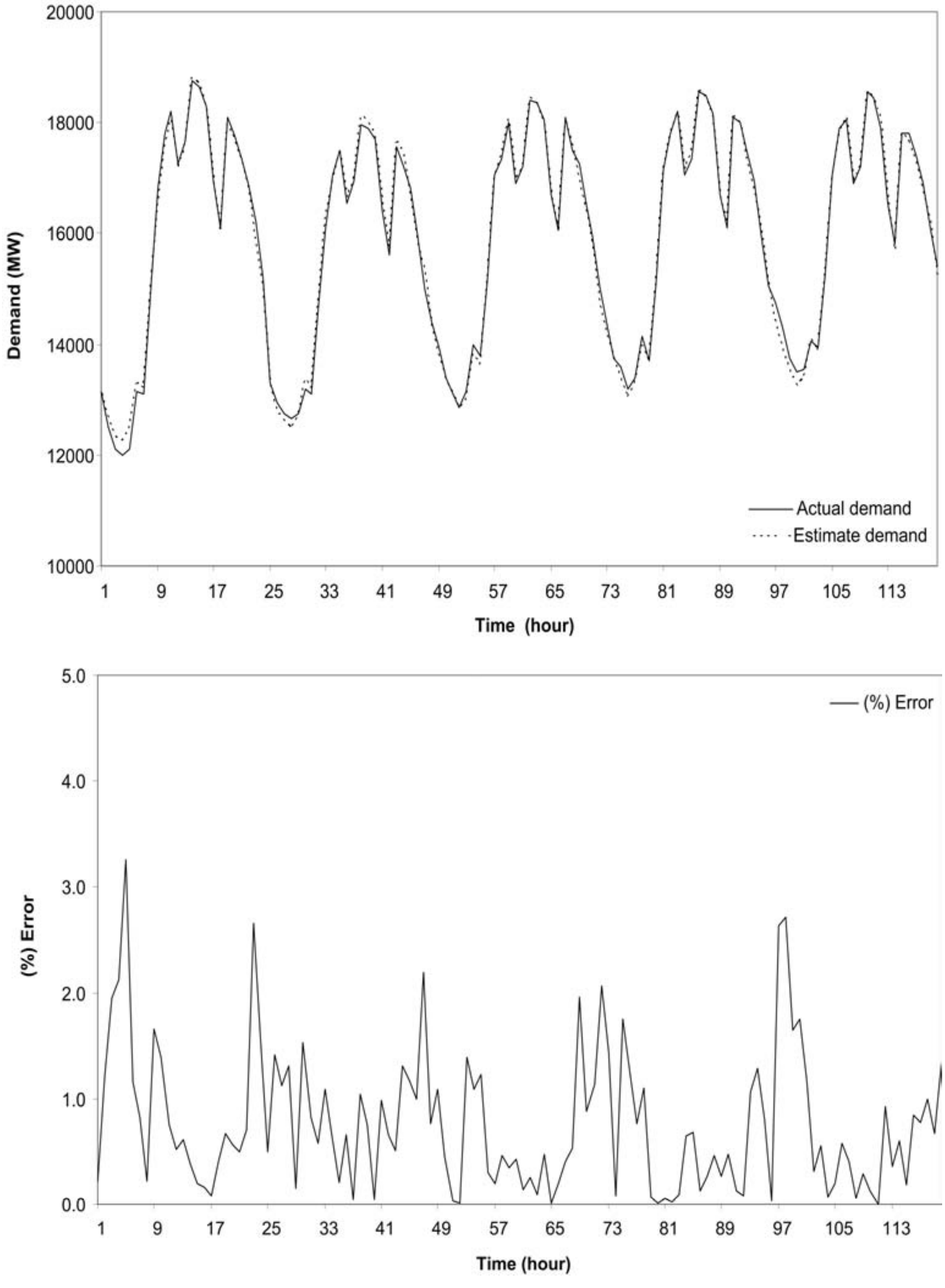

Figure A.1: Sample normal weekdays from 19-23 April 2004: (a) actual and estimated demand and (b) estimation error.

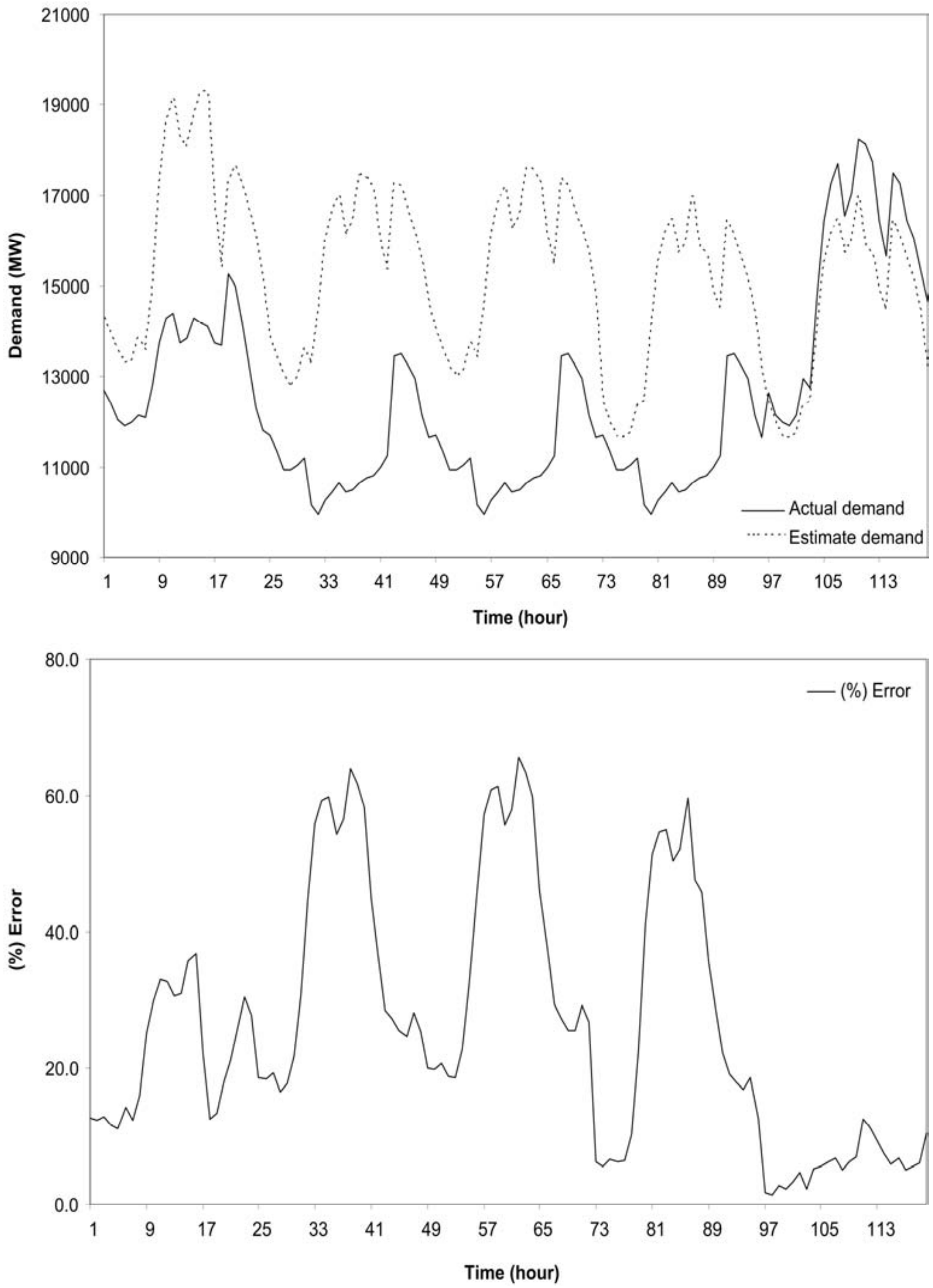

Figure A.2: Sample long holiday weekdays from 12-16 April 2004: (a) actual and estimated demand and (b) estimation error.

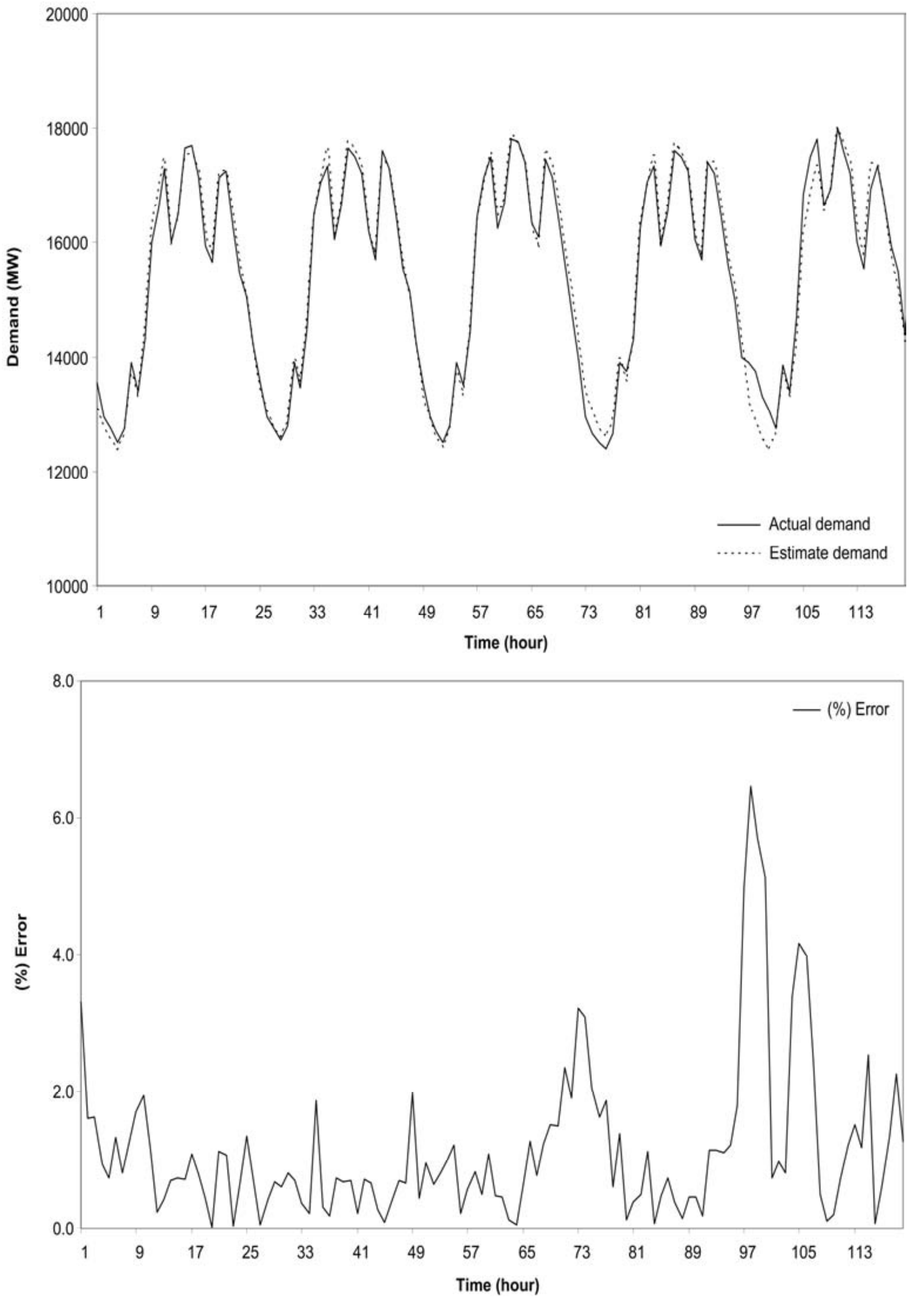

Figure A.3: Sample clear weekdays from 16-20 April 2004: (a) actual and estimated demand and (b) estimation error.

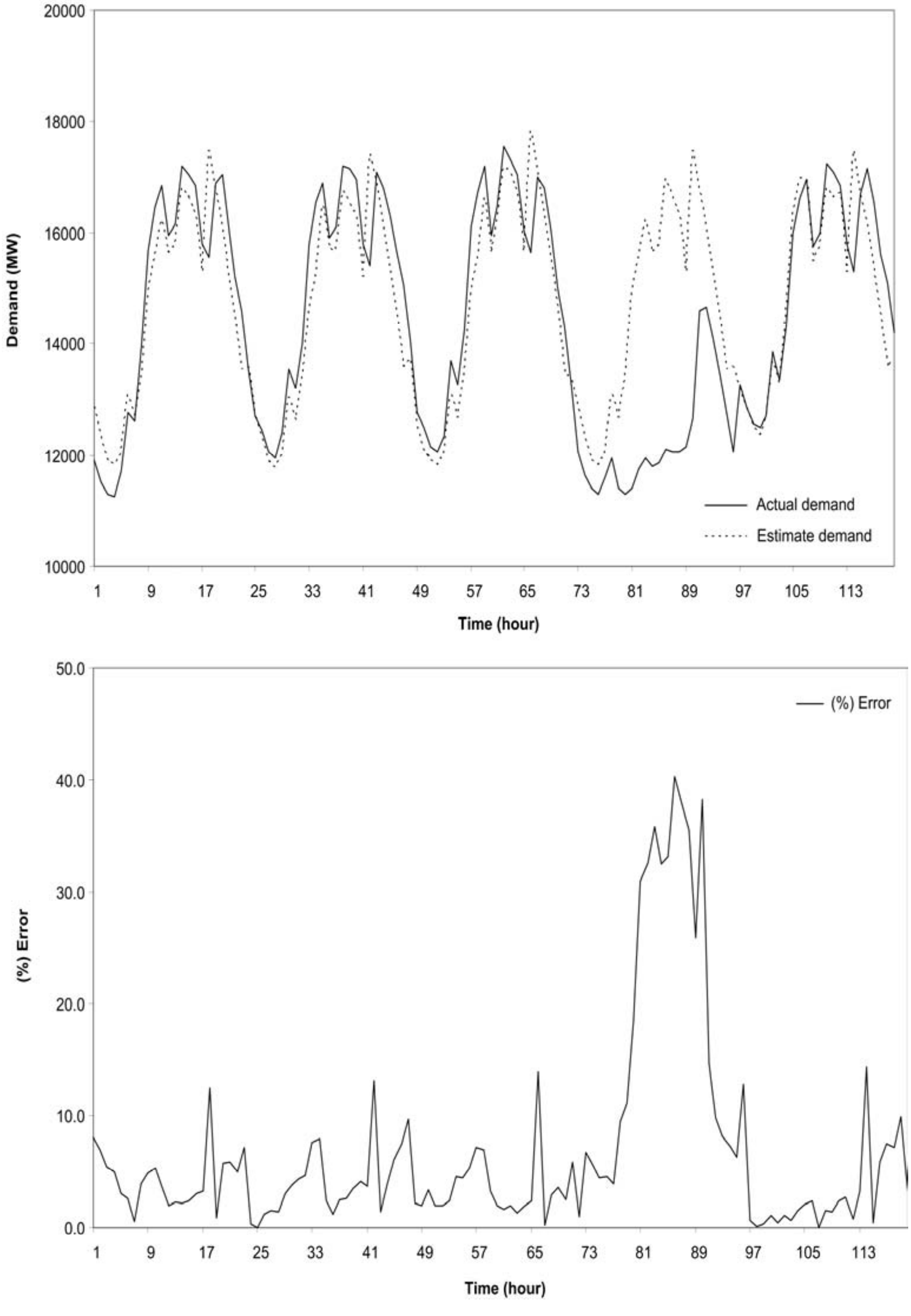

Figure A.4: Sample rainy weekdays from 9-13 April 2004: (a) actual and estimated demand and (b) estimation error.

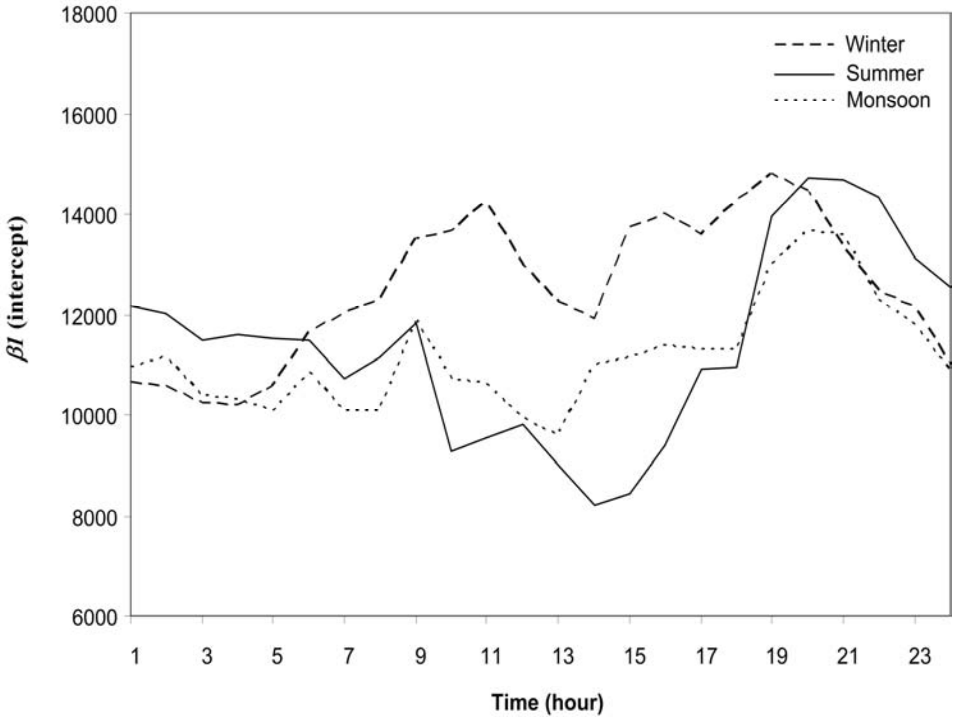

Figure A.5: Variations in the β_1 (intercept) over the seasons (winter, summer, and monsoon) for weekends.

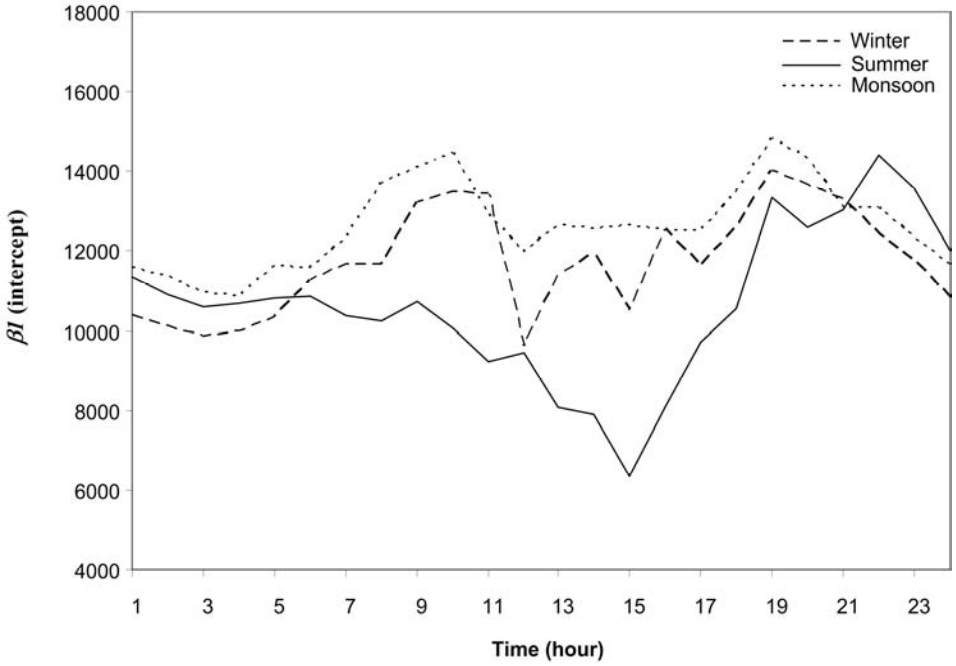

Figure A.6: Variations in the β_1 (intercept) over the season (winter, summer, and monsoon) by holiday.

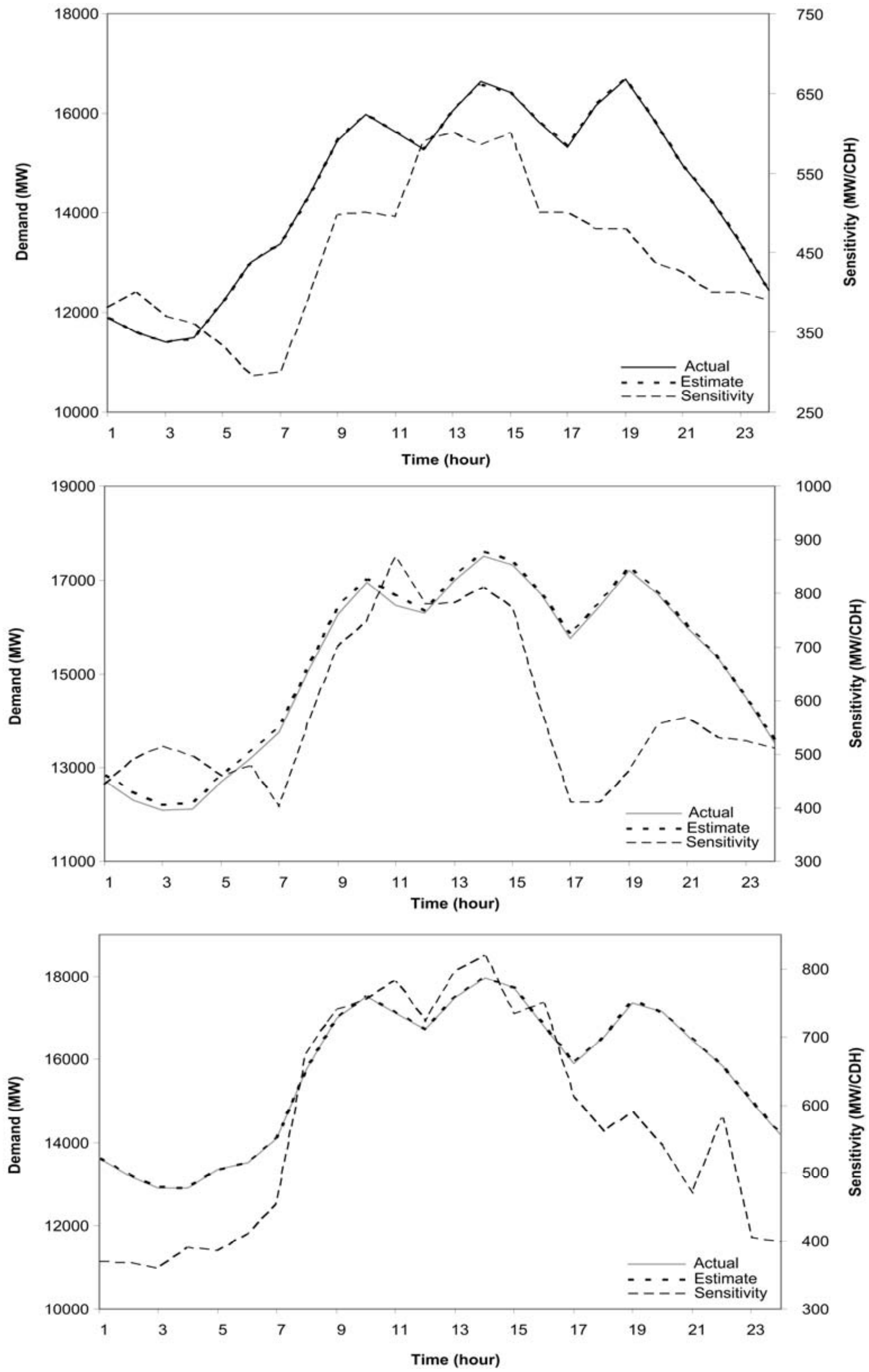

Figure A.7: Monthly mean actual and estimated demand and demand sensitivity for weekdays during February, March and May in 2004.

Time of day	February			March			May		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	380	0.76	2.05	442	0.40	4.10	370	0.84	1.22
1	400	0.84	1.59	490	0.62	2.75	368	0.82	1.33
2	369	0.83	1.57	514	0.68	2.50	360	0.79	1.44
3	360	0.84	1.52	496	0.74	2.09	390	0.78	1.38
4	332	0.70	1.33	460	0.70	2.42	386	0.86	1.04
5	295	0.90	0.74	477	0.78	1.82	410	0.72	1.16
6	300	0.92	0.53	402	0.71	1.91	453	0.79	1.14
7	392	0.89	0.96	564	0.60	2.41	675	0.70	1.68
8	497	0.85	1.14	700	0.77	1.96	740	0.60	2.06
9	500	0.82	1.27	746	0.67	1.70	754	0.57	2.15
10	495	0.90	0.65	870	0.78	2.06	782	0.74	1.57
11	590	0.95	0.79	780	0.77	1.73	722	0.78	1.33
12	600	0.96	0.65	781	0.82	1.46	797	0.75	1.72
13	585	0.97	0.82	810	0.71	1.70	819	0.50	2.31
14	600	0.97	0.46	771	0.68	1.84	734	0.42	2.13
15	500	0.98	0.35	580	0.77	0.99	750	0.50	1.91
16	500	0.94	0.50	411	0.90	0.77	610	0.53	1.49
17	480	0.96	0.46	410	0.83	0.82	561	0.60	1.18
18	479	0.96	0.45	467	0.78	1.01	590	0.75	0.86
19	438	0.93	0.69	556	0.85	0.92	540	0.60	1.02
20	424	0.84	1.16	568	0.93	0.77	470	0.50	1.15
21	400	0.84	1.78	530	0.91	0.97	581	0.40	1.49
22	400	0.62	2.58	525	0.94	0.85	405	0.60	1.70
23	390	0.73	2.46	510	0.85	1.72	398	0.70	0.99

Table A.1: Predicted regression coefficients and performance by monthly on weekday

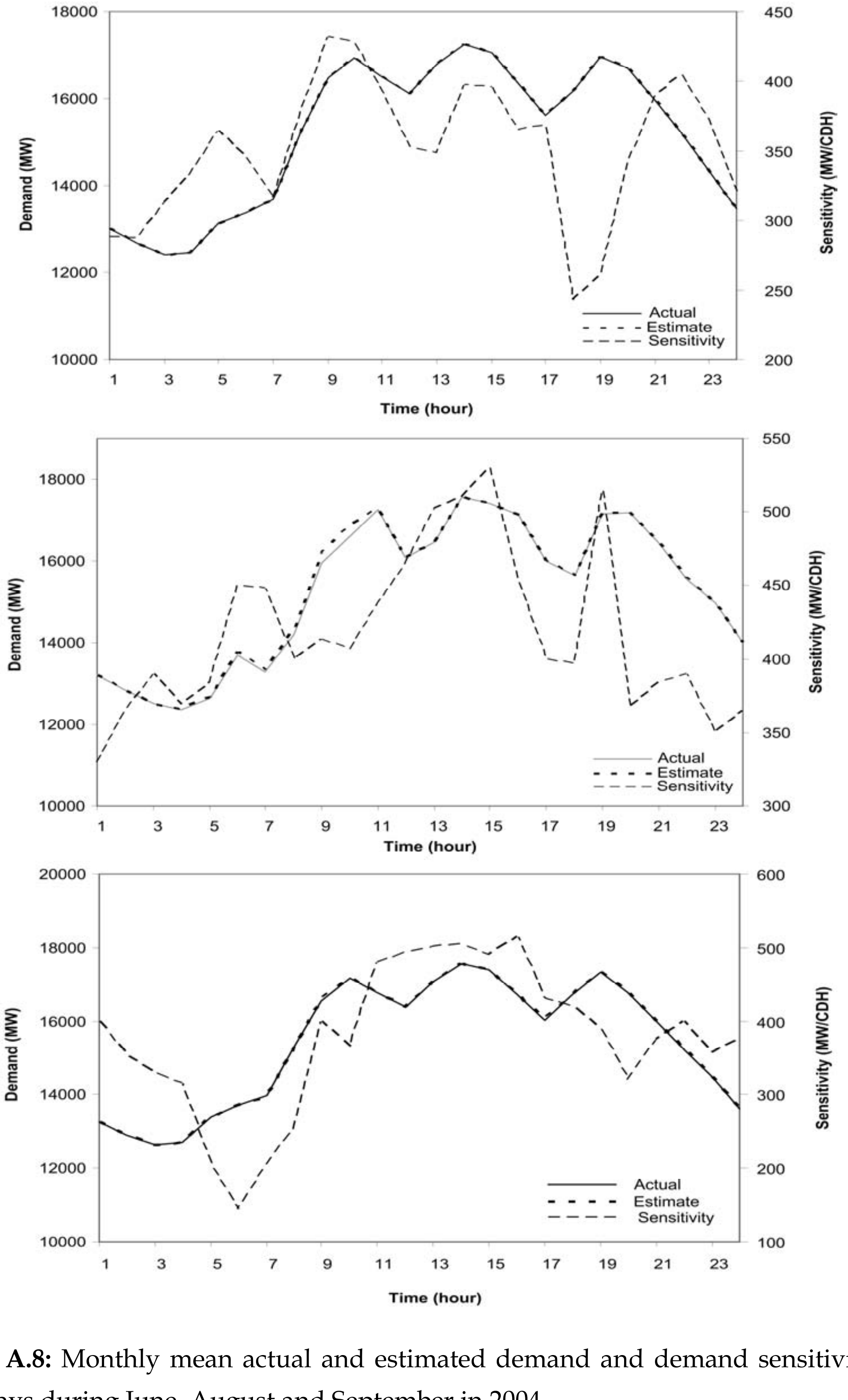

Figure A.8: Monthly mean actual and estimated demand and demand sensitivity for weekdays during June, August and September in 2004.

Time of day	June			August			September		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	288	0.83	0.98	330	0.20	3.19	400	0.50	1.91
1	287	0.90	0.76	364	0.20	2.96	353	0.60	1.55
2	313	0.92	0.69	390	0.30	2.63	328	0.75	1.04
3	334	0.90	0.68	369	0.30	2.39	315	0.87	0.56
4	364	0.97	0.42	384	0.40	1.83	204	0.70	0.54
5	345	0.97	0.36	450	0.40	1.90	145	0.97	0.14
6	316	0.90	0.47	448	0.30	1.74	205	0.92	0.27
7	378	0.81	0.65	400	0.30	1.86	255	0.50	1.08
8	432	0.70	0.93	413	0.40	2.07	400	0.72	0.63
9	428	0.67	1.13	407	0.30	2.13	365	0.93	0.21
10	393	0.66	1.07	438	0.50	1.35	480	0.93	0.38
11	353	0.68	0.95	465	0.90	0.44	493	0.92	0.41
12	348	0.71	0.97	502	0.94	0.40	501	0.86	0.49
13	397	0.65	1.05	510	0.91	0.51	505	0.90	0.39
14	396	0.80	0.78	530	0.92	0.46	490	0.96	0.24
15	365	0.79	0.60	453	0.89	0.48	514	0.65	0.72
16	369	0.80	0.34	400	0.85	0.56	430	0.54	1.05
17	243	0.82	0.53	397	0.85	0.54	421	0.68	0.77
18	260	0.82	0.62	515	0.87	0.70	390	0.80	0.44
19	341	0.84	0.66	367	0.65	1.07	321	0.20	1.59
20	390	0.82	0.96	384	0.61	1.11	375	0.20	2.41
21	405	0.73	1.42	390	0.60	1.36	400	0.20	2.57
22	372	0.68	1.40	350	0.50	1.49	357	0.20	2.92
23	321	0.70	1.24	365	0.65	1.46	377	0.20	3.22

Table A.2: Predicted regression coefficients and performance by monthly on weekday

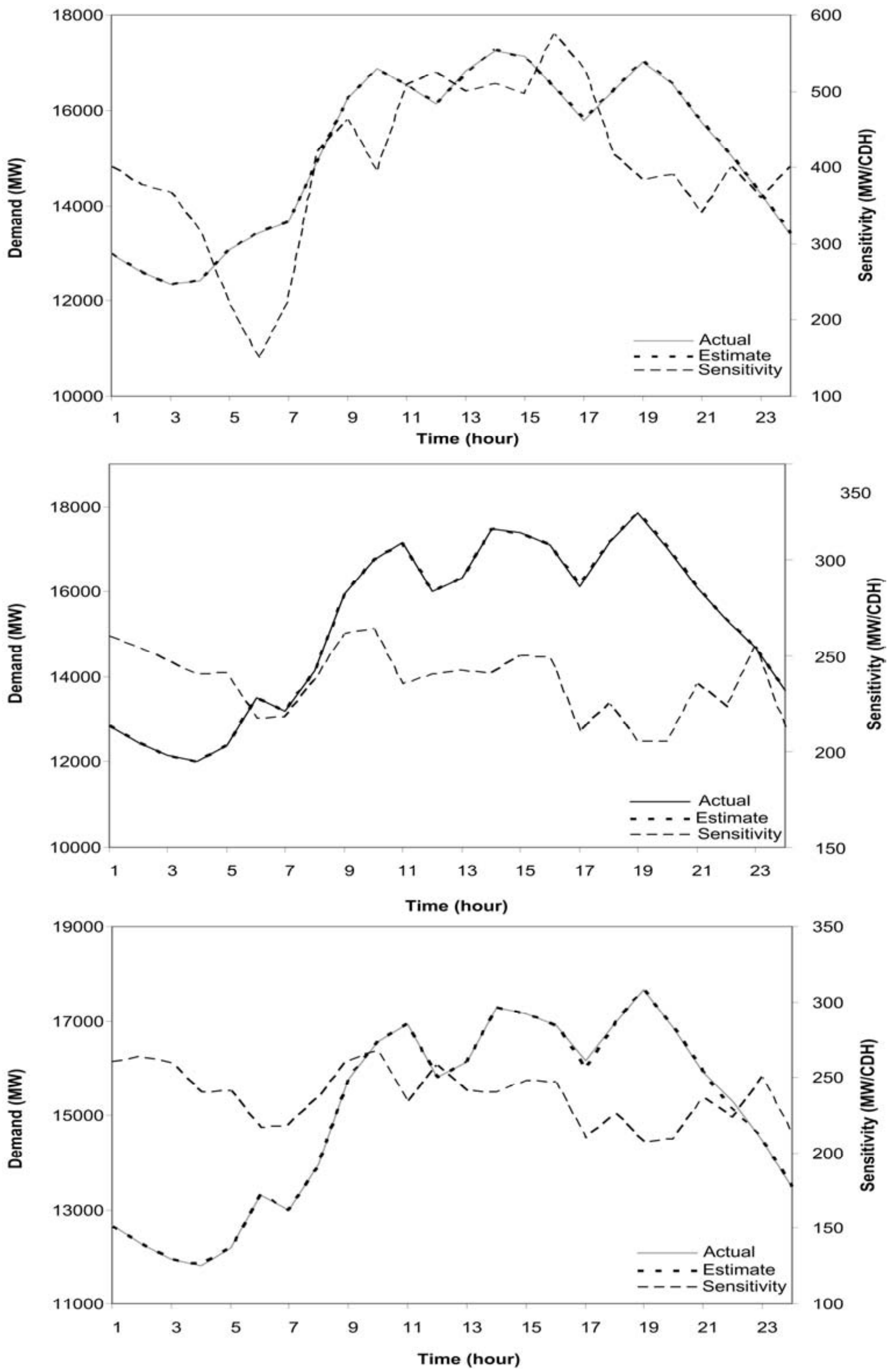

Figure A.9: Monthly mean actual and estimated demand and demand sensitivity for weekdays during October, November and December in 2004.

Time of day	October			November			December		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	400	0.60	1.91	260	0.87	0.96	260	0.91	0.98
1	377	0.63	1.55	254	0.88	1.12	264	0.92	1.13
2	367	0.78	1.01	247	0.87	1.14	259	0.90	1.15
3	316	0.87	0.57	240	0.86	1.07	240	0.90	1.08
4	220	0.78	0.52	241	0.91	1.03	241	0.93	1.04
5	150	0.95	0.16	217	0.87	1.07	217	0.87	1.09
6	225	0.90	0.19	218	0.88	0.79	218	0.88	0.81
7	420	0.40	1.24	237	0.96	0.39	237	0.98	0.39
8	463	0.70	0.74	261	0.89	0.75	261	0.89	0.76
9	395	0.90	0.26	264	0.95	0.68	268	0.95	0.66
10	508	0.94	0.39	235	0.96	0.39	233	0.95	0.39
11	524	0.93	0.45	240	0.94	0.49	258	0.96	0.47
12	500	0.97	0.43	242	0.95	0.71	241	0.90	0.69
13	510	0.96	0.17	241	0.95	0.48	240	0.94	0.48
14	496	0.94	0.25	250	0.95	0.51	248	0.93	0.53
15	575	0.62	0.83	249	0.91	0.55	247	0.93	0.58
16	530	0.53	1.18	210	0.94	0.36	210	0.96	1.17
17	417	0.62	0.77	225	0.78	0.80	226	0.82	0.81
18	383	0.76	0.43	205	0.89	1.02	207	0.67	1.01
19	390	0.33	1.45	205	0.83	0.93	209	0.75	0.94
20	340	0.20	2.55	235	0.79	1.51	237	0.77	1.54
21	400	0.20	2.72	223	0.70	1.99	223	0.62	2.33
22	359	0.20	3.06	255	0.72	1.50	250	0.71	1.52
23	400	0.20	3.30	212	0.83	1.51	212	0.71	1.53

Table A.3: Predicted regression coefficients and performance by monthly on weekday.

Time of day	Winter (2002)			Summer (2002)			Monsoon (2002)		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	268	0.30	1.23	420	0.73	0.96	300	0.68	1.03
1	335	0.40	1.12	530	0.80	1.15	300	0.73	1.13
2	318	0.48	1.01	550	0.74	1.40	335	0.76	1.10
3	330	0.66	0.98	529	0.78	1.30	360	0.63	1.30
4	450	0.68	0.87	490	0.80	1.46	340	0.69	0.89
5	430	0.69	0.90	477	0.87	1.30	400	0.73	1.09
6	450	0.72	0.70	500	0.88	1.40	300	0.80	0.81
7	450	0.71	1.24	590	0.82	0.98	260	0.81	0.97
8	540	0.70	1.23	669	0.86	0.75	350	0.80	0.76
9	600	0.65	0.96	559	0.84	0.80	375	0.78	0.80
10	610	0.75	0.71	620	0.87	0.85	470	0.85	0.94
11	560	0.87	0.73	614	0.89	0.79	450	0.84	0.60
12	500	0.81	1.30	685	0.89	0.71	435	0.87	0.61
13	600	0.80	1.45	720	0.90	0.78	500	0.85	0.48
14	580	0.84	1.50	630	0.91	0.90	400	0.90	0.53
15	510	0.62	1.69	520	0.91	1.10	430	0.93	0.58
16	650	0.53	1.18	490	0.94	1.40	330	0.96	1.17
17	660	0.52	2.20	520	0.78	0.80	300	0.82	0.81
18	400	0.59	1.97	610	0.75	1.02	300	0.67	1.01
19	354	0.61	1.45	680	0.71	0.93	350	0.75	0.94
20	444	0.63	1.78	630	0.79	1.51	425	0.77	1.54
21	450	0.57	1.30	600	0.70	1.99	350	0.62	2.33
22	390	0.49	1.67	520	0.72	1.50	350	0.65	1.31
23	380	0.52	1.70	500	0.67	1.51	400	0.60	0.87

Table A.4: Predicted regression coefficients and performance by winter, summer and monsoon for 2002 on weekday.

Time of day	Winter (2003)			Summer (2003)			Monsoon (2003)		
	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)	$\beta_{(CDH)}$	R^2	MAPE (%)
0	290	0.59	1.00	440	0.79	1.20	440	0.78	1.30
1	326	0.59	1.07	490	0.78	1.19	490	0.78	1.27
2	320	0.66	1.08	490	0.79	1.20	490	0.70	1.68
3	315	0.50	1.28	490	0.68	1.10	490	0.73	1.68
4	310	0.60	1.11	460	0.80	0.96	460	0.79	1.37
5	300	0.67	0.90	470	0.87	1.16	470	0.79	1.18
6	480	0.67	1.30	400	0.88	1.39	400	0.83	0.80
7	410	0.71	1.24	560	0.82	0.98	560	0.75	0.97
8	300	0.80	1.35	570	0.86	0.75	570	0.79	0.89
9	510	0.85	1.32	590	0.89	1.69	590	0.83	0.80
10	550	0.65	0.89	630	0.83	2.45	630	0.80	1.35
11	600	0.76	0.83	640	0.92	2.10	640	0.87	1.24
12	630	0.81	1.30	700	0.89	1.89	700	0.93	1.21
13	578	0.86	1.45	770	0.90	1.72	770	0.82	1.11
14	550	0.84	1.50	570	0.96	0.90	570	0.85	0.89
15	570	0.89	1.69	411	0.91	1.30	411	0.85	0.97
16	600	0.69	1.18	400	0.93	1.40	400	0.76	1.17
17	500	0.62	2.20	460	0.78	1.10	460	0.72	1.32
18	550	0.60	1.97	550	0.75	1.02	550	0.77	1.01
19	350	0.57	2.23	560	0.71	0.93	560	0.79	1.26
20	300	0.63	2.21	530	0.79	1.51	530	0.67	1.18
21	488	0.57	1.30	520	0.83	1.64	520	0.62	1.76
22	326	0.43	1.47	480	0.72	1.53	480	0.69	1.31
23	339	0.59	1.43	430	0.74	1.21	430	0.70	1.54

Table A.5: Predicted regression coefficients and performance by winter, summer and monsoon for 2003 on weekday.

Appendix B

The Details Projection Growth and Forecasts Demand

B1. The demand Predicted by A1, A2, B1 and B2

This investigates the potential impacts of climate change as given by the IPCC (SRES). GDP and population growth increase the electricity demand from the present time to the future (2020, 2050 and 2080). A significant variation in future annual demand compound growth rate was simulated in the four scenarios (A1, A2 B1 and B2) for the period 2010 to 2100. These combined to give a very significant matching pattern in absolute error as shown in the Figure A1 to B4.

Tables B1 to B4 show the comparison of projected change in compound growth rate of demand profiles for four scenarios for the simulations A1, A2, B1 and B2. The table provides the absolute error changes as the years progress. The tables show the comparison between the simulated results and SRES results.

The changes in temperatures projected by the Hadley Centre HadCM3 GCM are presented for the specific model in the Table B.5 to B.11. These figures show average monthly changes in maximum, minimum and mean daily temperature and demand for the 2020s, 2005s, and 2080s for the four scenarios (A1, A2, B1 and B2).

B2. Observed Climate Data (IPCC and SRES)

Yearly maximum, mean and minimum data for the view change in GCM fields relative to the 1961-1990 mean. Three time period are available: 2010-2039, 2040-2069 and 2070-2099 the available from the Data Distribution Centre (DDC) of the Intergovernmental Panel on Climate Change (IPCC). The DDC offers access to baseline and scenario data for representing the evolution of climatic, socio-economic, and other environmental conditions.

http://www.ipcc-data.org/

SRES Final Data in version 1.1, July 2000.

http://sres.ciesin.org/final_data.html

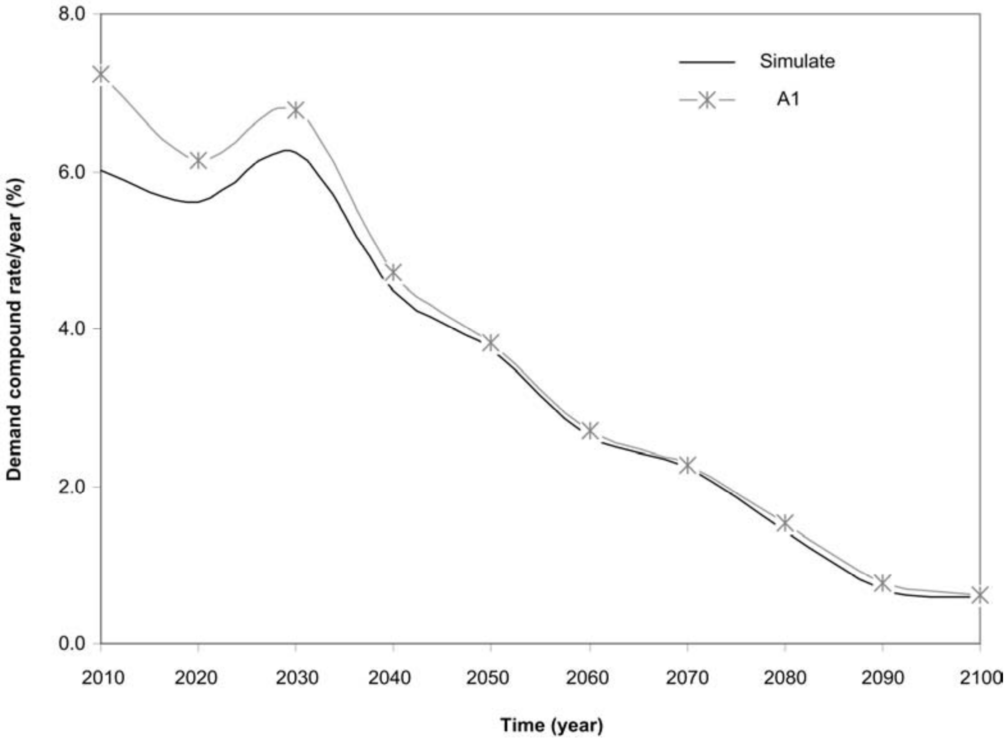

Figure B.1: Projected demand to 2100 for A1 scenario annual compound growth rate of demand (%) for 2010 to 2100.

Scenario	Model	10	20	30	40	50	60	70	80	90	100	All year
A1 AIM (%)	Sim	6.10	5.21	4.67	4.69	4.90	3.22	3.24	2.20	1.31	1.20	**3.67**
	SRES	7.32	5.81	4.94	5.01	5.01	3.29	3.29	2.30	1.32	1.32	**4.07**
A1 MESSAGE (%)	Sim	5.68	6.08	5.89	4.41	3.48	3.26	2.50	1.73	1.02	0.50	**3.46**
	SRES	6.17	6.85	6.37	4.61	3.52	3.34	2.57	1.80	1.09	0.50	**3.87**
A1 MINICAM (%)	Sim	6.54	5.73	5.41	4.27	3.40	2.34	1.72	1.21	0.41	0.45	**3.15**
	SRES	8.76	6.39	5.93	4.38	3.51	2.46	1.75	1.30	0.45	0.43	**4.20**
A1 ASF (%)	Sim	5.73	5.44	8.99	4.54	3.17	1.65	1.49	0.61	0.06	0.23	**3.19**
	SRES	6.68	5.50	9.88	4.88	3.27	1.77	1.50	0.75	0.15	0.15	**3.45**

Table B.1: A comparison of annual compound growth rate of demand (%) between four simulations and four A1 scenarios.

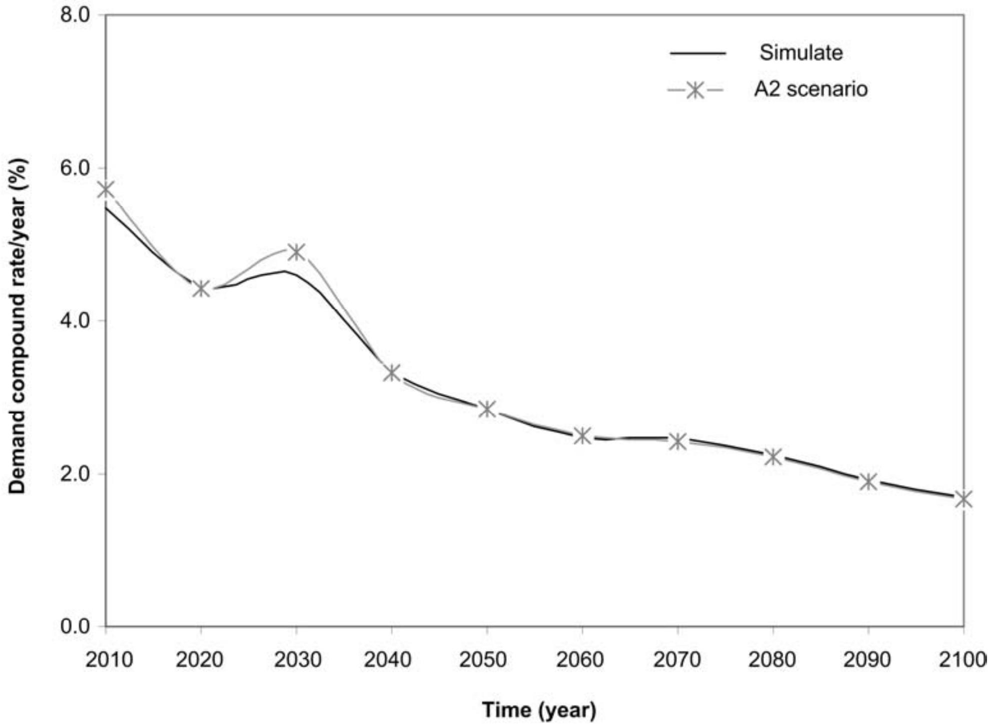

Figure B.2: Projected demand to 2100 for A2 scenario annual compound growth rate of demand (%) for 2010 to 2100.

Scenario	Model	10	20	30	40	50	60	70	80	90	100	**All year**
A2 AIM (%)	Sim	5.58	3.98	4.33	2.57	2.88	2.60	2.72	2.39	2.16	2.15	**3.14**
	SRES	6.11	3.72	4.70	2.68	2.68	2.67	2.67	2.40	2.14	2.14	**3.40**
A2 MESSAGE (%)	Sim	5.37	4.60	4.04	3.49	2.70	2.40	2.64	2.51	1.75	1.44	**3.09**
	SRES	5.31	4.79	4.18	3.30	2.84	2.34	2.67	2.51	1.72	1.39	**3.21**
A2 MINICAM (%)	Sim	5.89	4.66	3.07	3.16	2.96	3.09	2.85	2.55	2.33	1.95	**3.25**
	SRES	6.91	5.05	3.05	3.04	2.85	3.12	2.84	2.57	2.40	1.94	**4.10**
A2 ASF (%)	Sim	5.04	4.61	6.94	4.13	2.86	1.85	1.67	1.58	1.43	1.27	**3.14**
	SRES	4.53	4.19	7.65	4.29	2.99	1.86	1.57	1.46	1.36	1.20	**3.26**

Table B.2: A comparison of annual compound growth rate of demand (%) between four simulations and four A2 scenarios.

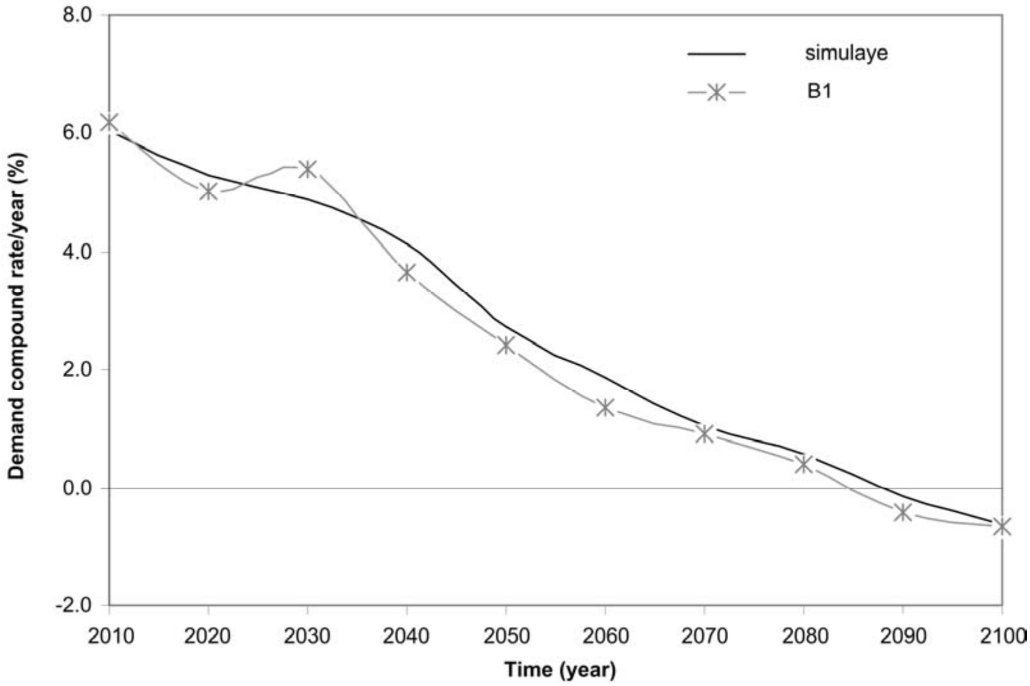

Figure B.3: Projected demand to 2100 for B1 scenario annual compound growth rate of demand (%) for 2010 to 2100.

Scenario	Model	10	20	30	40	50	60	70	80	90	100	All year
B1AIM (%)	Sim	6.27	5.63	4.58	5.97	3.81	2.66	1.13	0.93	0.04	-0.74	**3.03**
	SRES	5.99	4.66	6.58	3.94	2.82	1.15	1.03	0.13	-0.73	-0.79	**2.95**
B1 MESSAGE (%)	Sim	5.50	4.76	4.04	3.27	1.39	1.40	0.44	0.44	-0.31	-0.96	**2.00**
	SRES	5.83	5.52	4.50	3.65	1.48	1.58	0.51	0.57	-0.13	-0.84	**2.46**
B1 MINICAM (%)	Sim	6.91	6.37	5.00	3.73	2.98	2.42	1.52	1.04	0.63	-0.17	**3.04**
	SRES	6.97	5.31	3.91	3.07	2.55	1.58	1.09	0.72	-0.17	-0.17	**3.12**
B1 ASF (%)	Sim	5.45	4.35	5.85	3.55	2.70	0.98	1.03	-0.14	-1.01	-0.68	**2.21**
	SRES	5.99	4.66	6.58	3.94	2.82	1.15	1.03	0.13	-0.73	-0.79	**2.48**

Table B.3: A comparison of annual compound growth rate of demand (%) between simulations and B1 scenarios.

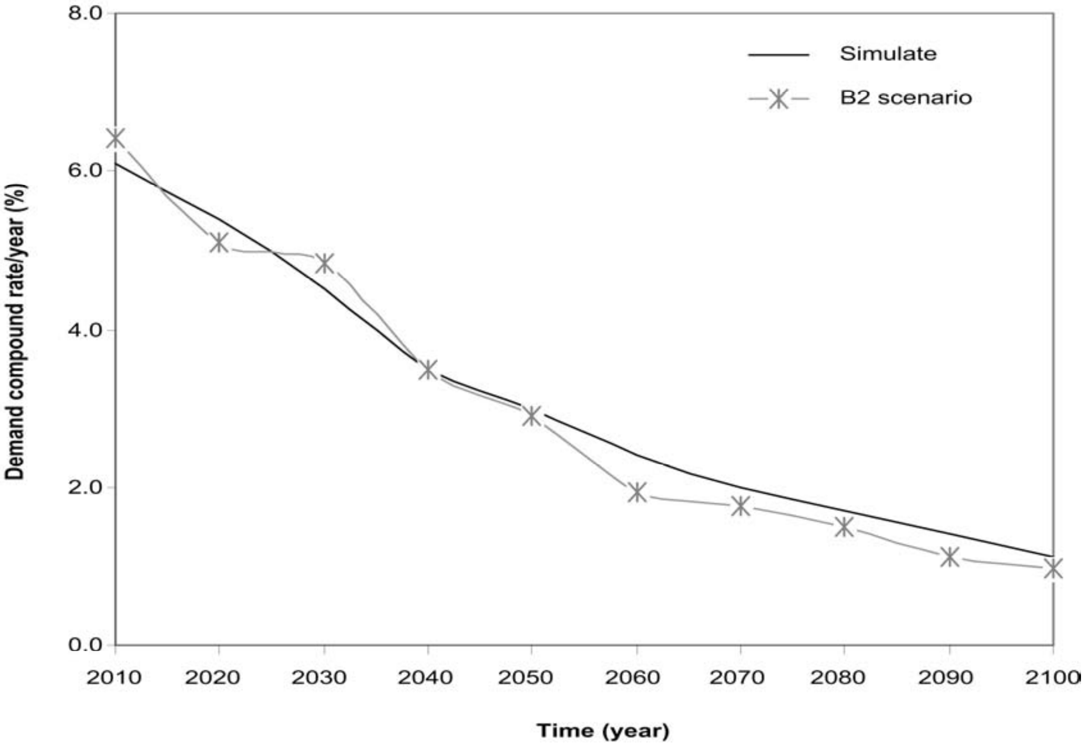

Figure B.4: Projected demand to 2100 for B2 scenario annual compound growth rate of demand (%) for 2010 to 2100.

Scenario	Model	10	20	30	40	50	60	70	80	90	100	All year
B2 AIM (%)	Sim	5.97	4.63	4.35	2.95	3.27	2.27	2.37	1.75	1.28	1.29	**3.54**
	SRES	6.97	5.03	4.68	3.25	3.25	2.29	2.29	1.73	1.17	1.17	**3.39**
B2 MESSAGE (%)	Sim	5.84	5.87	5.34	4.34	3.49	2.71	2.26	2.16	1.96	1.48	**3.70**
	SRES	6.22	5.66	4.49	3.59	2.75	2.24	2.15	1.98	1.43	1.11	**3.45**
B2 MINICAM (%)	Sim	7.38	6.87	5.22	3.99	3.30	2.82	2.48	2.00	1.66	1.30	**2.38**
	SRES	7.34	5.46	4.09	3.37	2.87	2.53	2.02	1.69	1.28	1.13	**3.85**
B2 ASF (%)	Sim	5.17	4.11	5.44	3.46	2.57	0.67	0.84	0.77	0.76	0.78	**3.11**
	SRES	5.15	4.20	6.05	3.74	2.72	0.67	0.63	0.58	0.54	0.51	**2.48**

Table B.4: A comparison of annual compound growth rate (%) in demand between simulations and SRES predicted.

Scenario A1	Years	Variable	Temperature rise (°C) month from IPCC												Overall
			Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	
	Current	Max	27.7	28.7	31.3	32.3	31.9	31.6	32.1	31.4	29.5	29.5	32.3	32.3	30.9
	2004	Mean	26.7	26.8	29.7	31.2	30.8	29.9	30.9	30.0	28.4	28.4	29.2	29.2	29.3
		Min	25.1	24.7	28.0	29.8	29.0	27.9	29.7	28.6	27.3	27.4	25.2	25.2	27.3
		Max	28.7	30.4	32.4	32.9	32.3	33.1	32.7	32.0	30.1	30.3	33.5	33.4	31.8
	2020	Mean	27.7	28.4	30.7	31.8	31.2	31.5	31.5	30.6	28.9	29.2	30.3	30.4	30.2
		Min	26.1	26.1	28.9	30.3	29.3	29.6	30.2	29.2	27.8	28.1	26.3	26.4	28.2
		Max	30.1	33.1	34.5	34.2	33.6	33.1	33.6	32.9	31.2	31.4	34.6	34.8	33.1
	2050	Mean	29.0	30.8	32.8	33.1	32.5	31.5	32.4	31.6	30.0	30.3	31.5	31.7	31.4
		Min	27.2	28.2	30.9	31.5	30.6	29.6	31.1	30.1	28.9	29.1	27.4	27.6	29.4
		Max	32.3	35.3	37.0	35.9	34.9	34.6	34.9	34.3	32.4	32.7	36.4	36.8	34.8
	2080	Mean	31.3	33.1	35.2	34.7	33.8	32.8	33.7	32.9	31.1	31.6	33.3	33.7	33.1
		Min	29.4	30.5	33.0	33.0	31.8	30.6	32.4	31.4	29.9	30.4	29.3	29.6	30.9

Table B.5: Average monthly changes in mean, maximum and minimum temperatures from IPCC (Hadley Centre GCM)

Scenario A1	Years	Variable	Demand increase (MW) month from IPCC												Overall
			Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	
	Current	Max	14127	15292	16421	16752	16270	15833	15805	16098	16209	15909	16111	15844	15889
	2004	Mean	13511	14397	15251	16092	15746	15237	15318	15347	15483	15207	15265	14999	15154
		Min	12285	13468	13532	15276	13915	14183	14749	14620	14936	14636	14135	13863	14133
		Max	14556	16009	16700	17000	16511	16280	15916	16055	16064	15890	16213	16016	16101
	2020	Mean	14104	15110	15747	16400	15917	15711	15479	15510	15634	15458	15476	15287	15486
		Min	13331	14114	14744	15605	14854	15026	15038	14939	15258	15039	14518	14330	14733
		Max	15206	17236	17884	17690	17240	16280	16275	16455	16475	16359	16486	16335	16660
	2050	Mean	14730	16211	16927	17096	16655	15711	15830	15897	16052	15910	15741	15598	16030
		Min	13888	15073	15901	16261	15590	15026	15366	15314	15667	15466	14771	14628	15246
		Max	16253	18238	19372	18592	18019	16823	16768	17002	16928	16862	16909	16825	17383
	2080	Mean	15792	17243	18343	17991	17409	16183	16316	16434	16480	16433	16186	16087	16741
		Min	14916	16063	17169	17081	16277	15395	15828	15824	16046	15981	15222	15100	15908

Table B.6: Average monthly changes in mean, maximum and minimum demand from IPCC (Hadley Centre GCM)

Scenario	Years	Variable	Temperature rise (°C) month from IPCC												Overall
A2			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
	Current	Max	27.7	28.7	31.3	32.2	31.8	31.6	32.0	31.4	29.4	29.5	32.3	32.3	30.9
	2004	Mean	26.7	26.8	29.7	31.1	30.7	29.9	30.8	30.0	28.3	28.4	29.2	29.2	29.2
		Min	25.1	24.7	28.0	29.7	28.9	27.9	29.6	28.6	27.2	27.3	25.1	25.2	27.3
		Max	28.3	29.5	31.9	32.5	32.5	32.2	32.7	32.0	30.1	30.3	33.3	33.1	31.5
	2020	Mean	27.4	27.6	30.3	31.4	31.3	30.5	31.5	30.6	28.9	29.2	30.2	30.0	29.9
		Min	25.8	25.5	28.6	29.9	29.5	28.5	30.2	29.2	27.8	28.1	26.1	26.0	27.9
		Max	29.7	30.4	32.7	33.1	32.9	33.2	33.4	32.9	31.0	31.2	34.2	34.2	32.4
	2050	Mean	28.7	28.5	31.1	32.0	31.7	31.5	32.2	31.6	29.8	30.1	31.1	31.1	30.8
		Min	26.9	26.5	29.3	30.4	29.8	29.4	30.9	30.1	28.7	29.0	27.1	27.0	28.8
		Max	31.5	32.3	34.4	35.1	34.5	34.1	34.6	33.7	31.8	32.1	35.7	36.1	33.8
	2080	Mean	30.5	30.4	32.8	34.0	33.4	32.4	33.3	32.3	30.6	31.0	32.6	33.0	32.2
		Min	28.7	28.3	30.9	32.3	31.5	30.4	32.0	30.8	29.4	29.9	28.5	28.8	30.1

Table B.7: Average monthly changes in mean, maximum and minimum temperatures from IPCC (Hadley Centre GCM)

Scenario A2	Years	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Overall
			Demand increase (MW) month from IPCC												
	Current	Max	14127	15292	16421	16719	16214	15761	15739	16046	16163	15863	16044	15844	15853
	2004	Mean	13511	14397	15251	16045	15681	15163	15250	15291	15405	15131	15199	14999	15110
		Min	12285	13468	13532	15219	13896	14130	14678	14563	14846	14546	14063	13863	14091
		Max	14359	15601	16427	16788	16617	15978	15918	16058	16064	15894	16171	15935	15984
	2020	Mean	13920	14767	15521	16201	16024	15374	15480	15511	15634	15458	15434	15199	15377
		Min	13171	13837	14566	15423	14965	14658	15037	14937	15258	15038	14474	14235	14633
		Max	15011	16000	16880	17100	16856	16342	16207	16455	16429	16255	16379	16209	16343
	2050	Mean	14549	15179	15955	16501	16247	15703	15760	15897	15988	15830	15654	15465	15727
		Min	13740	14270	14984	15704	15152	14952	15297	15314	15595	15403	14706	14490	14967
		Max	15881	16843	17852	18203	17790	16642	16631	16772	16700	16647	16740	16656	16946
	2080	Mean	15432	16012	16922	17599	17193	16042	16176	16201	16264	16210	16008	15909	16331
		Min	14594	15085	15924	16714	16091	15316	15690	15596	15854	15761	15044	14916	15549

Table B.8: Average monthly changes in mean, maximum and minimum demand from IPCC (Hadley Centre GCM)

Scenario	Years	Variable	Temperature rise (°C) month from IPCC												Overall
B1			**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	
	Current	Max	27.7	28.7	31.3	32.2	31.8	31.6	32.0	31.4	29.5	29.4	32.3	32.3	30.9
	2004	Mean	26.7	26.8	29.7	31.1	30.7	29.9	30.8	30.0	28.4	28.3	29.2	29.2	29.2
		Min	25.1	24.7	28.0	29.7	28.9	27.9	29.6	28.6	27.3	27.2	25.1	25.2	27.3
		Max	28.6	29.3	31.8	32.7	32.3	32.2	32.5	32.0	30.0	29.9	33.1	33.5	31.5
	2020	Mean	27.5	27.4	30.2	31.6	31.2	30.5	31.3	30.6	29.0	28.7	30.0	30.2	29.8
		Min	25.9	25.3	28.4	30.1	29.3	28.5	30.1	29.2	27.9	27.6	25.9	25.9	27.9
		Max	29.5	30.1	32.5	33.2	32.8	32.6	33.1	32.4	30.6	30.4	33.8	34.6	32.1
	2050	Mean	28.5	28.2	30.9	32.1	31.7	30.9	31.9	31.0	29.5	29.3	30.7	31.1	30.6
		Min	26.8	26.0	29.2	30.7	29.9	28.9	30.7	29.5	28.4	28.2	26.7	26.6	28.6
		Max	29.9	30.8	33.3	34.2	33.6	33.0	33.3	32.9	31.2	31.0	34.3	34.9	32.7
	2080	Mean	28.9	28.9	31.6	33.1	32.5	31.5	32.1	31.6	30.1	29.8	31.1	31.5	31.2
		Min	27.1	26.8	29.9	31.5	30.5	29.5	30.9	30.2	29.0	28.7	27.0	27.0	29.2

Table B.9: Average monthly changes in mean, maximum and minimum temperatures from IPCC (Hadley Centre GCM)

Scenario B1	Years	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Overall
			Demand increase (MW) month from IPCC												
	Current	Max	14127	15292	16421	16719	16214	15761	15739	16046	15863	16163	16044	15844	15853
	2004	Mean	13511	14397	15251	16045	15681	15163	15250	15291	15131	15405	15199	14999	15110
		Min	12285	13468	13532	15219	13896	14130	14678	14563	14546	14846	14063	13863	14091
		Max	14489	15520	16321	16883	16511	15978	15861	16058	15794	15995	16128	16024	15963
	2020	Mean	14020	14683	15412	16296	15917	15374	15421	15511	15377	15563	15389	15244	15351
		Min	13221	13749	14454	15521	14854	14658	14978	14937	14974	15185	14426	14222	14598
		Max	14923	15875	16742	17183	16829	16102	16082	16232	16032	16203	16296	16283	16232
	2050	Mean	14460	15019	15842	16599	16238	15510	15643	15668	15605	15776	15566	15466	15616
		Min	13652	14070	14896	15813	15176	14804	15193	15078	15184	15400	14614	14392	14856
		Max	15099	16197	17195	17690	17268	16273	16160	16433	16289	16429	16402	16364	16483
	2080	Mean	14639	15351	16276	17096	16664	15704	15721	15894	15835	15988	15654	15553	15865
		Min	13826	14418	15311	16261	15565	15019	15267	15331	15391	15595	14681	14489	15096

Table B.10: Average monthly changes in mean, maximum and minimum demand from IPCC (Hadley Centre GCM)

Scenario	Years	Variable	Temperature rise (°C) month from IPCC												Overall
B2			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
	Current	Max	27.7	28.7	31.3	32.3	31.9	31.6	32.1	31.4	29.5	29.5	32.3	32.3	30.9
	2004	Mean	26.7	26.8	29.7	31.3	30.8	29.9	30.9	30.1	28.4	28.4	29.2	29.2	29.3
		Min	25.1	24.7	28.0	29.8	29.0	27.9	29.7	28.7	27.3	27.4	25.1	25.2	27.3
		Max	28.6	29.7	32.1	32.9	32.6	32.2	32.7	32.0	30.1	30.0	33.1	32.9	31.6
	2020	Mean	27.5	27.8	30.5	31.8	31.5	30.5	31.5	30.6	28.9	29.0	30.0	29.8	30.0
		Min	25.9	25.7	28.8	30.3	29.7	28.5	30.2	29.2	27.8	27.9	25.9	25.8	28.0
		Max	29.1	30.0	32.5	33.3	33.0	32.9	33.3	32.6	30.6	30.9	33.6	33.6	32.1
	2050	Mean	28.1	28.2	30.9	32.1	31.9	31.1	32.0	31.2	29.5	29.7	30.5	30.5	30.5
		Min	26.5	26.1	29.1	30.6	30.0	29.0	30.7	29.7	28.4	28.6	26.5	26.6	28.5
		Max	30.0	30.8	33.5	33.8	33.6	33.4	33.8	33.1	31.2	31.4	34.6	34.7	32.8
	2080	Mean	29.0	28.9	31.8	32.7	32.5	31.7	32.6	31.7	30.0	30.3	31.5	31.7	31.2
		Min	27.3	26.8	30.1	31.1	30.5	29.6	31.3	30.3	28.9	29.1	27.4	27.7	29.2

Table B.11: Average monthly changes in mean, maximum and minimum temperatures from IPCC (Hadley Centre GCM).

Scenario B2	Years	Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Overall
			Demand increase (MW) month from IPCC												
	Current	Max	14127	15292	16421	16719	16214	15761	15739	16046	16163	15863	16044	15844	15853
	2004	Mean	13511	14397	15251	16045	15681	15163	15250	15291	15405	15858	15199	15844	15241
		Min	12285	13468	13532	15219	13896	14130	14678	14563	14846	15863	14063	15844	14365
		Max	14489	15683	16534	16983	16725	15978	15916	16055	16064	15794	16126	15890	16020
	2020	Mean	14020	14851	15630	16397	16132	15374	15479	15510	15634	15377	15389	15154	15412
		Min	13221	13925	14678	15621	15069	14658	15038	14939	15258	14974	14429	14189	14667
		Max	14728	15841	16774	17201	16932	16214	16138	16304	16271	16146	16254	16060	16238
	2050	Mean	14279	15015	15846	16602	16340	15574	15689	15742	15843	15687	15521	15332	15623
		Min	13503	14098	14872	15800	15274	14808	15228	15154	15465	15246	14566	14376	14866
		Max	15184	16197	17301	17496	17268	16398	16341	16528	16496	16359	16486	16315	16531
	2080	Mean	14724	15351	16385	16900	16664	15774	15896	15970	16055	15910	15741	15597	15914
		Min	13908	14418	15419	16078	15565	15026	15430	15386	15658	15466	14771	14648	15148

Table B.12: Average monthly changes in mean, maximum and minimum demand from IPCC (Hadley Centre GCM)

Appendix C

List of Publications

During the period of research the following papers and journals have been published and/ or presented at conference:

C.1 International Refereed Journal Papers

1. Parkpoom, S., Harrison, G.P. and Bialek, J.W., 2005. Climate and weather uncertainty in the electricity industry, *International Energy Journal*. 6 (1), part 4, pp. 55-64.
2. Parkpoom, S. and Harrison, G.P., 2006. Using weather sensitivity to forecast Thailand's electricity demand., *International Energy Journal* (except on the publication).
3. Parkpoom, S. and Harrison, G.P., 2007. Analyzing the Impact of Climate Change on Future Electricity Demand in Thailand, *IEEE Transactions on Power Systems,* (except on the publication).

C.2 International Conference Papers

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Climate and Weather Uncertainty in the Electricity Industry

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Abstract

The short-term variability of weather patterns and, over the longer term, of climate has a significant impact on the generation, transmission and demand for electricity. Utilities traditionally managed these effects through central planning and vertical integration. In the long term, sufficient plant was planned and constructed to meet anticipated peak demand, whilst the costs of dealing with short-term variability were absorbed and passed on to consumers. With deregulation, the need to manage weather and climate effects has changed dramatically (e.g. imbalance penalties for incorrectly predicted demand). In the longer term, there is a risk that climate change will alter the availability of renewable energy resources, adversely affecting the financial viability of such plant. This paper examines the extent of climatic and weather-related uncertainty affecting the electricity industry and reviews currently available techniques of assessing and managing both short and long term risks.

1. Introduction

Short-term weather variability and, longer term, climate variability has a major impact on the generation, transmission and demand for electricity. Pre-deregulation, utilities generally managed to limit weather and climate impacts through central planning and vertical integration. In the long term, sufficient plant was planned and constructed to meet anticipated peak demand, whilst the costs arising from short-term variability were absorbed and passed on to consumers. With deregulation market participants are becoming exposed to these effects. Hence, there is greater need to manage the impact of weather and climate uncertainty.

Weather is defined as the atmospheric conditions existing over a short period in a particular location. It is often difficult to predict and can vary significantly even over a short period. Climate on the other hand, is generally viewed as the average weather conditions over a long-term period (say 30 years) for a defined area. It varies from place to place, depending on latitude, distance to the sea, etc. Climate also varies in time: seasonally, annually and on a decadal basis. The difference between weather and time can be summed up by "weather tells you what clothes to wear but climate tells you what clothes to buy" [1].

This paper reviews the basis for climate change and the projections for South East Asia. It examines the sensitivity of the electricity supply industry to weather variability and in the longer term to climate change and variability.

2. Climate Change

The state of the Earth's climate is largely affected by heat stored in the atmosphere and oceans. Processes that affect this heat storage can cause the Earth's climate to change. Greenhouse gases (e.g. Carbon Dioxide, CO_2) in the atmosphere tend to trap heat and, whilst changes in levels have occurred naturally over history, it is the extent of man-made greenhouse gas emissions that are causing concern, given the potential to significantly and rapidly alter climate. For the past few hundred years and, particularly from the mid-20th Century, the burning of fossil fuels and deforestation have released increasing quantities of greenhouse gases.

During the last 100 years, global mean temperatures have risen by almost 1°C with much of the warming in the past few decades. Further increases in man-made greenhouse gas emissions are likely to increase the warming by between 1.4 and 5.8°C by 2100 [2]. Figure 1 shows the historic and range of projected future temperature rise and clearly shows that the rate of increase has accelerated.

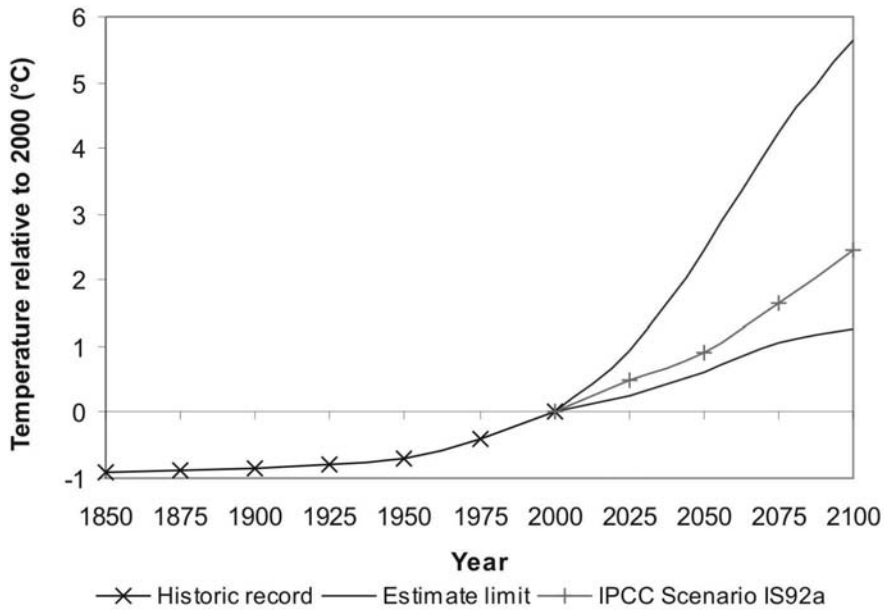

Figure1. Historic and expected range of future temperature rise (adapted from [3, 4])

Projections of climate change are often based on the output of General Circulation Models (GCMs), complex numerical models that simulate physical processes in the oceans and atmosphere. There is a wide variation in the output from such models, partly due to the range of input assumptions made. Table 1 shows a sample of scenarios from the IPCC's Special Report on Emission Scenarios (SRES) covering the period of 1990 to 2100 [2]. These include socio-economic estimates (e.g. GDP), the resulting CO_2 levels and the consequent changes in global temperatures and sea levels.

They project changes in a range of climatic variables that have the potential to have significant impacts on a range of sectors in every region.

Date	Global Population (billions)	Global GDP (10^{12} US$/yr)	CO_2 Concentration (ppm)	Global Temperature Change (ºC)	Global Sea-level Rise (cm)
1990	5.3	21	354	0	0
2000	6.1-6.2	25-28	367	0.2	2
2050	8.4-11.3	59-187	463-623	0.8-2.6	5-32
2100	7.0-15.1	197-550	478-1099	1.4-5.8	9-88

Table 1. SRES scenarios and the implications for CO_2 level, climate and sea level [2]

3. Climate Change in South East Asia

GCM simulations project that the climate in Asia as a whole will undergo an annual mean warming of 3ºC by the 2050s and 5ºC by the 2080s. Accompanying this, an annual mean precipitation increase of 7% and 11% will be seen by the 2050s and 2080s, respectively [5].

The projections for tropical South East Asia are less severe but are still significant, with, for example, mean annual temperature and precipitation rising by some 3% and 8.5%, respectively, by the 2080s [5]. However, these figures mask anticipated seasonal changes. Figure 2 shows the anticipated trend in annual and seasonal temperatures over this century; the greater increase in winter temperatures is clear. Figure 3 shows the corresponding patterns for precipitation which indicate stronger changes in winter precipitation.

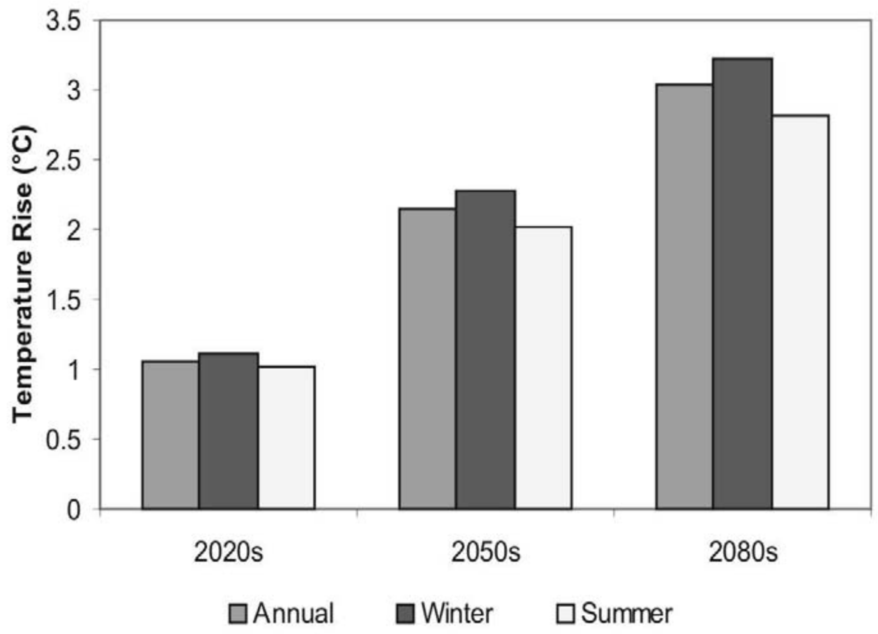

Figure 2. Plausible changes in temperature in tropical South East Asia [5]

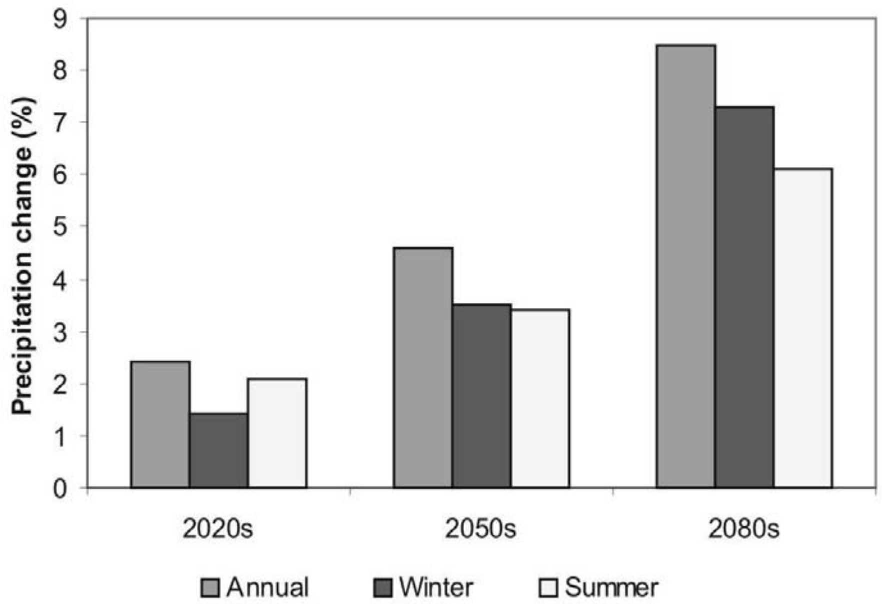

Figure 3. Plausible changes in precipitation in tropical South East Asia [5]

Changes of these magnitudes are likely to have significant impacts in South East Asia, given the high population density and low standard of living. It is anticipated that there will be a rising demand for forestry, agriculture and livestock products and it is likely that there will also be an increased risk of fire, typhoons/tropical storms, floods and landslides. Table 2 shows a representative sample of the major climate risks in South East Asia. In addition to these broad risks, there are several impacts that will be felt within the electricity industry.

Risk in South East Asia from Climate Change	Confidence Level
Increased vulnerability of climate-dependent sectors affecting the economy.	Medium
The large deltas and coastal low-lying areas will be inundated by sea-level rise.	High
The frequency of forest fires in will increase.	Medium
Increased precipitation intensity during the monsoon increases flood risk in temperate/tropical areas.	Medium
Drier conditions in arid/semi-arid areas during summer, leading to more severe droughts.	Medium
Climate change and variability could exacerbate existing extreme climate vulnerabilities in temperate/tropical areas.	High

Table 2. Examples of climate change risk in South East Asia [5]

4. Impacts on Generation

4.1 Thermal power Generation

Thermal generation (i.e. fossil/nuclear powered) could be affected by climate change. Climate variables are known to have an influence on the efficiency of thermal electric generation plants. The basic efficiency of both steam and gas cycles are defined by their Carnot efficiency which is governed by the difference between the hot source (combusted fuel) and cold sink (ambient) temperatures in the thermodynamic cycle. Higher air temperature will raise the temperature of the sink hence decreasing the efficiency and capacity ratings of combustion turbines. Increases in high temperatures and humidity will also be detrimental to electricity generation from gas, oil, or nuclear steam cycles, which rely on cooling towers for the condensing process. In most cases

the overall effect of global warming on thermal power production is likely to be small, with one US utility estimating efficiency reductions of between 0.1 and 0.2% [6].
Nuclear power plants might be relatively more sensitive to climate change as they are designed for operation within certain temperature ranges and some plants have been forced to close down on extremely hot days. Climate change might require modification to allow such plants to continue to operate in warmer temperatures [6]. In addition, a climate change induced reduction in river flow could also reduce the efficiency or even require a plant to shut down if inadequate water is available for cooling purposes. Such effects were seen in France in the summer of 2003 when several days of extreme temperatures threatened production from nuclear stations. The overall effect will, of course, depend upon the location of the power plant and the construction techniques used.

Other than efficiency impacts, thermal plant located along rivers or on the coast could be at risk from flooding or sea level rise. There is some evidence that climate change will lead to an increase in cyclone activity and intensity and also monsoon intensity which could pose a threat to plant, particularly on the coast.

4.2 Hydropower

The hydroelectric potential is defined by the river flow, and therefore changes in flow due to climate change will alter the energy potential. Importantly, hydroelectric schemes are designed for a particular river flow distribution, hence; plant operation may become non-optimal under altered flow conditions. Climate change could affect the amount and seasonality of flow in most rivers in South East Asia affecting the magnitude and timing of production.

Hydropower has received the most attention in climate impact studies as it is the widest sued renewable resource and is vulnerable to changes in several climatic variables. Studies reported in [7] examined climate impacts in the Mekong delta (among other international rivers) under a range of potential GCM scenarios. Figure 4 shows the effect of a 5°C degree rise in mean annual temperature accompanied by a 4%

rise in precipitation as simulated by the UK Hadley Centre GCM. As can be seen, there are significant increases in several months. While such an increase would appear to be beneficial for hydropower production, the systems ability to harness the increased flows depends on whether sufficient turbine capacity or storage exists.

Changes in river flow and consequently production will have a significant impact on plant revenue stream and ultimately will affect what has been termed 'willingness to develop' [8], i.e. investment attraction. A series of studies [9-11] for a planned hydropower scheme in Sub-Saharan Africa examined how climate change could affect the attractiveness of the scheme as an investment. The scheme's financial viability was shown to be sensitive to changes in precipitation and temperature, that GCM scenarios implied a deterioration in project returns and, that project risk appeared to increase.

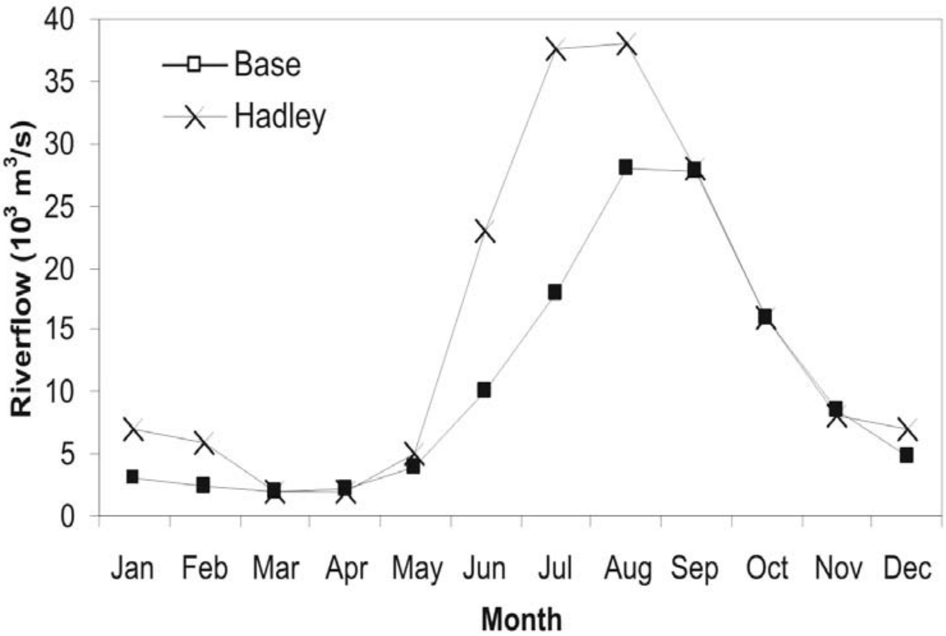

Figure 4. Historic (Base) and projected river flows at location in Lower Mekong Basin for Hadley Centre scenario (adapted from [7])

4.3 Other Renewable Energy Sources

The potential implications of rising greenhouse gases have increased the interest in energy generated by other renewable sources such as wind power and solar. Currently, South East Asia obtains approximately 80% of its energy from fossil fuels, but many countries have programmers to develop their wind and solar resources. These too will not be immune to climatic effects.

A small but increasing number of studies (e.g. [12]) have considered how wind power would be influenced by global warming. A change in climate might, for example, modify the density and duration of speed wind in a specific area. Large-scale changes in climate zones will also change wind characteristic. However, changes in extreme events such as storms, hail will influence the damage these will have on wind power generation structures and facilities. The impacts of climate change on wind power production are difficult to quantify as changes are extremely difficult to assess.

Changes in cloudiness that result from humidity changes may also affect the production potential of photo-voltaic (PV) cells. Given that production can be reduced to as little as 5% under cloudy conditions, increased cloud cover could be detrimental.

4.4 Overall Sensitivity

The sensitivity of generation to climate change depends very much on the mix of technologies used in a given system. Using Thailand as an example, Figure 5 shows the generation mix expected from the present up to 2017. This shows that the current dominance of fossil fuels will wane and by 2017 a third of production is anticipated from renewable plant. There would appear to be potentially more scope for supply difficulties where renewable technologies have been shown to be sensitive to climate variables.

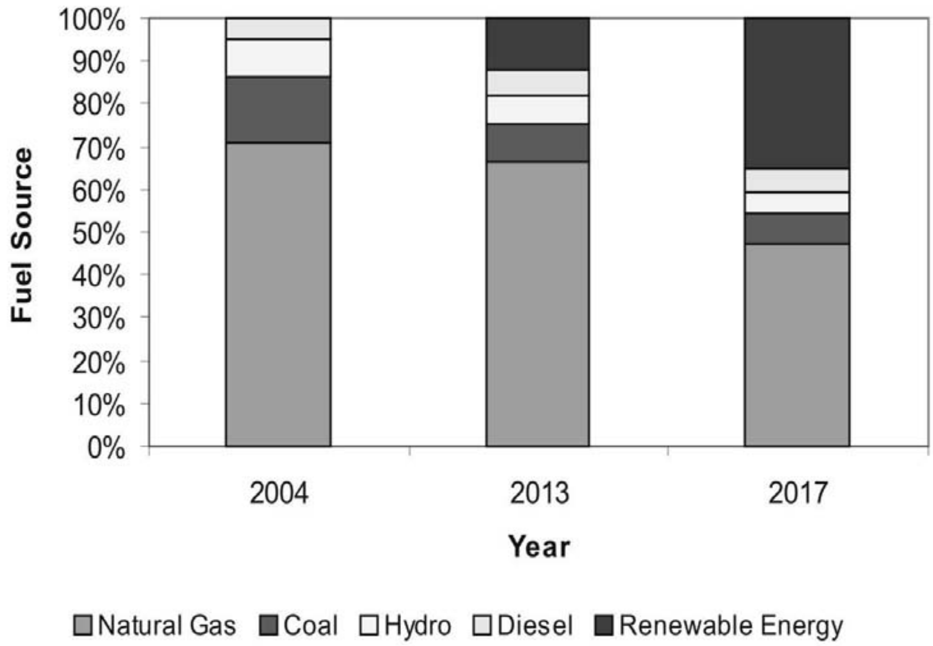

Figure 5. Forecast generation fuel mix in Thailand to 2017 [13]

5. Climate Impacts on Transmission

Atmospheric conditions affect the power flow rating of transmission and distribution lines and are traditionally specified by national or international standards such as those published by the IEEE [14]. The thermal rating of a line is governed by a maximum allowable conductor temperature in order to prevent excessive sagging. The conductor temperature is influenced not only by the ohmic heating effect but also ambient temperature, isolation and wind speed, of which temperature is the dominant climatic variable. Hence higher temperatures will tend to reduce transmission capacity, worsening existing network constraints and necessitating load curtailment or expensive network upgrades.

Extreme weather is also problematic for transmission systems: high winds, heavy rain and lightning can all create faults on the system. The management of these requires investment [15]. Extremely cold conditions can also create problems to which the Canadian ice storms of 2000 are testament. With an expectation of a greater frequency and intensity of extreme weather there is the potential for greater damage to the system and consequent supply interruptions.

6. Impacts on Electricity Demand

The potential impact of future changes in climate on electricity demand can be seen on a daily basis through the fluctuation of demand with weather conditions. In liberalised systems such as the UK, suppliers must accurately predict weather conditions in order to manage their supply contacts. Where they fail to do so, they are exposed to significant imbalance penalties. As such, it is area that is receiving much research attention (e.g. [16]) and has spawned interest in financial market derived techniques such as weather derivatives. As electricity demand globally is expected to grow by at least 5% by 2015 [17] and, as climate change becomes more prevalent, it will be essential for those charged with managing demand to take account of future changes.

Electricity demand is influenced not only by temperature but also wind speed, humidity, precipitation and cloud cover. These influence demand for air-conditioning, space heating, refrigeration and water pumping loads which will add to both peak and 24-hour demand. The peak loading is particularly important as on occasions of extreme temperatures this is likely to stress electricity systems in meeting demand. Again, France in 2003 is a good example of conditions where extremely hot temperatures gave rise to a significant increase in air-conditioning – at the very time that output from nuclear stations was limited by cooling limitations – threatening blackouts.

The impact on other uses of electricity can be significant: water-pumping requirements will increase where the climate change becomes warmer but not wetter as water demand from irrigation, residential, commercial and municipal sectors will rise. Refrigeration requirements would increase and water-heating requirements would decrease, although the direct effects are likely to be significantly less than the effects on space conditioning. Refrigeration and water-heating equipment is often located in conditioned spaces and thus are not affected by outdoor temperature changes. Additionally, refrigeration equipment evaporator coil temperatures are lower than those of air conditioning equipment and water heaters operate significantly hotter than room temperatures, the proportionate impact will be lower.

The impacts on electricity demand also depend on the mix of resources used for heating and cooling. If air conditioning is produced using electricity but space heating is provided by gas boilers, then global warming will increase electricity demand but overall energy use could decrease.

Clearly the degree to which electricity demand in a given country might be sensitive to changes in climate will depend very much on its climate type and its level of economic development. In high latitude countries like the UK, warmer climates will tend to reduce space heating demand. In lower latitudes cooling loads will increase with, for example, South East Asian electricity demand expected to increase by 5 to 10% [5] as a result.

Figure 6 shows the current breakdown between various uses of electricity in the domestic sector in Thailand. With its hot, humid climate, a major portion of domestic electricity use (39%) is for cooling food or accommodation. This portion would be expected to increase as Thailand's economy grows more affluent.

While figures are not available for how Thai domestic demand might change with climate change, we can extract some information from projections for the UK (Figure 7) and from projections of Thai peak demand over the next 15-20 years (Figure 8). At present, the UK has little domestic air-conditioning load hence it is not represented in Figure 7. However, this is expected to rise although the increase will depend on complex sociological factors and is difficult to project. An indication of the potential increase is highlighted in the commercial sector which has seen 5% growth in the last five years and expects to see a further 6% rise to 2010 [15]. The rise in refrigeration usage is, however, fairly clear. Figure 8 shows a projection of peak demand in Thailand. Apart from the marked increase in overall demand levels it is clear that summer peak demand rises proportionately more. This reflects increasing economic development and a likely corresponding use of air-conditioning equipment.

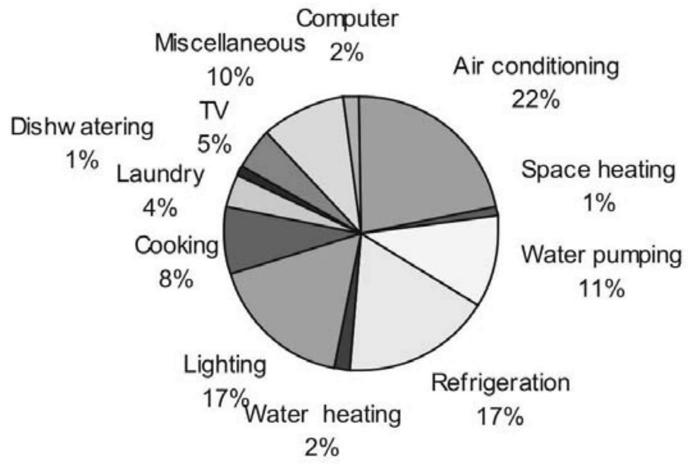

Figure 6: Thai domestic electricity demand in 2003 [18]

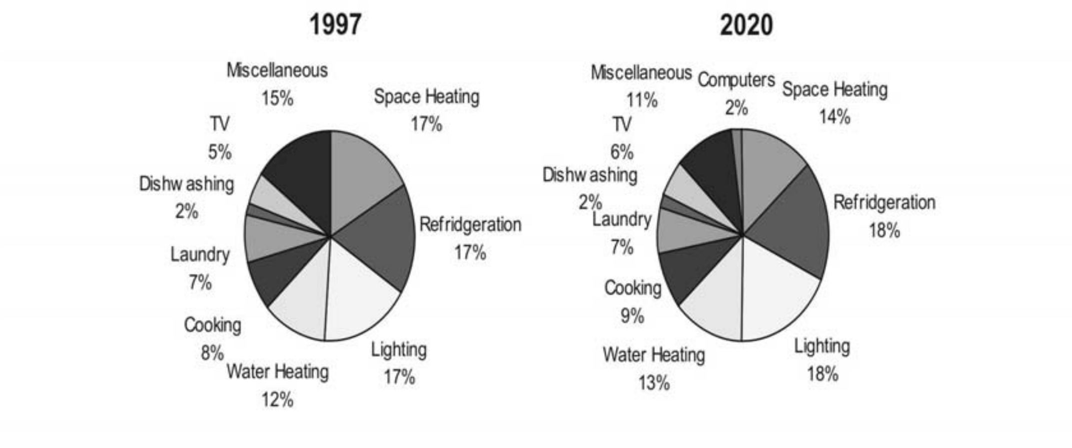

Figure 7. UK domestic electricity demand in 1997 and forecast for 2020 [15]

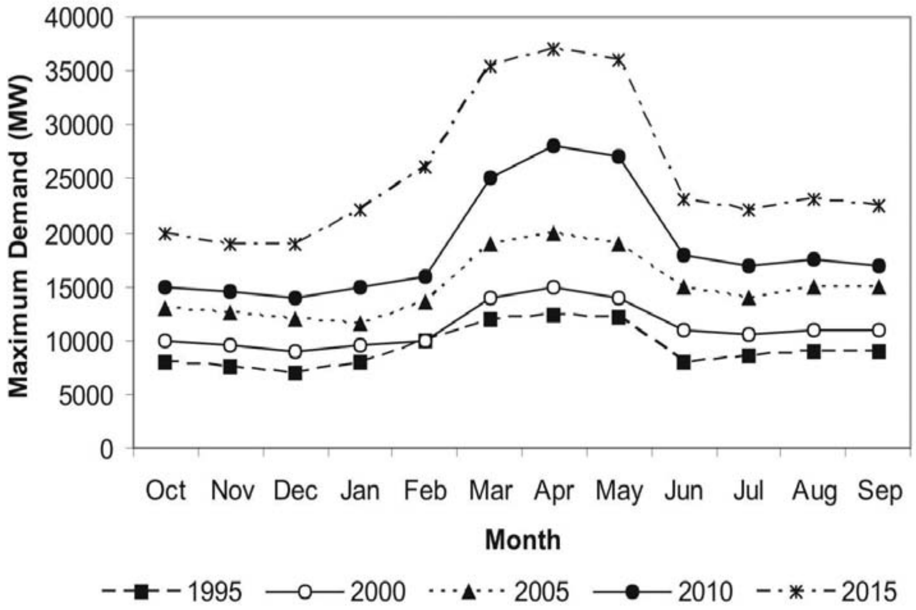

Figure 8. Maximum electricity demand curves for Thailand [13]

7. Discussion

As the previous sections indicate, there are many areas of the electricity supply industry that are sensitive to the variability of the weather. Pre-deregulation, utilities managed weather effects through vertical integration and either absorbing costs within the organisation as a whole or, where possible, passing them on to consumers.

With deregulation, individual market players are exposed to weather effects. With an increasing emphasis on risk analysis and management, players are increasingly looking for ways to minimise or eradicate weather effects from their revenue and cost streams. These include improved forecasting techniques or risk transfer through insurance or in weather markets.

In the long term, climate change will necessitate similar approaches in analysing, planning and financing future investment in generation, transmission and demand. However, the commonly used assumption that the future will be similar to the past does not hold. As such, new techniques need to be developed and implemented that can take account of future climate uncertainty.

To this end, future work will be addressing several aspects of potential climate impacts that are particularly relevant for developing nations in South East Asia. These are likely to include:
analysis of future demand patterns, and
analysis of future generation availability given an increasing input from renewable resources.

8. Conclusion

This paper reviews the basis for climate change and the projections for South East Asia. It details a range of generating technologies that are sensitive to weather conditions and, in the long-term, vulnerable to changes in climate. Impacts include changes in the availability and timing of resources, impacts on conversion efficiency and variations in the economics of plant. Transmission systems are also found to be sensitive through thermal constraints and faults caused by extreme weather conditions. Demand levels are also weather-dependent as UK experience indicates.

Variations in weather and climate pose potentially serious challenges to many areas of the electricity supply industry. With deregulation, players are becoming more exposed to variations. Accordingly, they must assess the uncertainty surrounding both short and long term variations, examine the impacts and plan and manage them effectively.

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